UNIVERSITY OF CAPE COAST

MIXING METAPHORS, MODIFIERS AND AFFECT TOWARDS SENTIMENT EVALUATION

BY

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DECLARATION

Candidate's Declaration

I hereby declare that this thesis is the result of my own original research and that no part of it has been presented for another degree in this university or elsewhere.

Candidate's Signature:..................................... Date: 4th August, 2021

Name: Linda Amoako

Supervisors' Declaration

We hereby declare that the preparation and presentation of the thesis were supervised in accordance with the guidelines on supervision of thesis laid down by the University of Cape Coast.

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ABSTRACT

The use of figurative language, with a major emphasis on metaphors and a minor emphasis on oxymorons, has been widely accepted as part of everyday language, not just in literary language. Over the last few years, there has also been a large move towards automated sentiment analysis through which diverse corporations seek feedback on the sentiment (or affect: emotions, value judgments, etc.) that customers bear towards their goods and services. The need for this feedback has been particularly challenged by the use of social media, which allow the use of non-literal language, including shorthand, abbreviations and emoticons. Beginning with an overview of metaphors, sentiment analysis, modifiers, and how they relate to each other in terms of conveying affect, this thesis examines the accuracy of relying on lexical libraries like SentiWordNet and WordNet in an attempt to extract sentiment-related information on language in discourse. Following a set of empirical studies and experiments, I examined how some existing systems are carrying out analysis of metaphors and oxymorons, and how those systems evaluate metaphors that have made use of modifiers. I demonstrate that modifiers do enhance the sentiment conveyed by metaphors, though their placement within the metaphor, if not done well, can distort the intended meaning, providing a good motivation for non-literal text identification systems to be integrated into existing sentiment analysis systems. I also prove by analysis that SentiWordNet has inherent inaccuracies that introduce errors in sentiment extractions, and recommend that it is crucial to identify non-literal text before sentiment is extracted in order to avoid incorrect judgments.

KEYWORDS

Metaphors

Modifiers

Natural Language Processing

Oxymorons

Sentiment Analysis

SentiWordNet

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DEDICATION

To my family. You are simply the best!

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LIST OF ABBREVIATIONS

AI	Artificial Intelligence
BNC	British National Corpus
CMT	Conceptual Metaphor Theory
FSA	Free Sentiment Analyzer
GloWbE	Global Web-based English corpora
IDLE	Integrated Development Environment
ISR	Intuitive Sentiment Rating
KWIC	Key Word in Context
MIP	Metaphor Identification Procedure
MIPVU	Metaphor Identification Procedure Vrije Universiteit
ML	Machine Learning
MRWs	Metaphor-Related Words
NLP	Natural Language Processing
NLTK	Natural Language Toolkit
POS	Part-Of-Speech
RQ	Research Question
SA	Sentiment Analysis
SO	Semantic Orientation
SVM	Support Vector Machine
SWN	SentiWordNet
VADER	Valence Aware Dictionary and Sentiment Reasoner
WN	WordNet
WSD	Word Sense Disambiguation

WWW	World Wide Web

CHAPTER ONE

INTRODUCTION

1.1 Background to the Study

Over the last few years, the use of technology for all manner of things has vastly increased. One of the key technologies that have emerged in the effort to help people navigate the huge amount of user-generated content online is sentiment analysis (Pang and Lee, 2005). Sentiment analysis, which is also sometimes referred to as opinion mining, uses Natural Language Processing (also referred to as NLP, and is a branch of AI which is concerned about enabling computers with enough understanding in order to allow a seamless interfacing between computers and the natural language of humans in both written and spoken contexts), Computational Linguistics (a sub area of linguistics where computer science techniques are used to analyse and synthesize language and speech), and Text Analytics (referring to a process of drawing quality information and meaning from written text) to extract subjective materials from source materials.

This project is about metaphors in discourse, the impact of modifiers on the sentiment evaluations of metaphors, sentiment analysis (SA), and how some existing automated Sentiment Analysis systems cope with literary devices, specifically metaphors and two-word oxymorons. Some issues arising from this research include the inaccuracies of major lexical libraries like SentiWordNet, and how they affect the quality of sentiment extracted from it, a challenge for which I propose using extensive crowdsourcing to enhance the extracted sentiment. I also propose incorporating metaphor and oxymoron-detection tools into existing sentiment analysis systems to enhance systems' ability to identify and evaluate non-literal text before affect detection is carried out.

1.2 Statement of the Problem

Due to the deep integration of literary devices like metaphor and oxymorons in everyday language, it is possible to find, for example, metaphoric phrases being used in an attempt to explain other metaphors. It is the case that in such situations, an automated attempt at extracting meaning and/or sentiment from the text will results in errors if the text is read in a literal sense. It is therefore important to identify such devices in communication before natural language techniques are employed to interpret them.

1.3 Research Questions

In my study, I examine (in a very broad sense) the effect of modifiers on the affect component of metaphors and oxymorons used in discourse, and see how some affect-extracting systems handle the identification and interpretation of modifiers, if they do. I will achieve this by carrying out a series of empirical studies that are aimed at answering the research questions (RQs) outlined as follows:

RQ1: To what extent do some current Sentiment Analysis systems cope with modifiers?

To answer this question, I will carry out an experiment to determine how affect is evaluated in modifiers using some Sentiment Analysis systems. Here, a list of modifiers will have their sentiment values examined, and the studies done will seek to answer the following sub questions:

a. To what extent are adverbs in themselves sentiment-laden?

b. How do sentiment scores of adverbs reflect their corresponding definitions?

c. Is there a differentiation between adverbs of manner that are used to *report* sentiment and those that are used to *express* sentiment?

d. What are the implications of having a differing intuitive sentiment score from the machine-computed score?

Recommendations will then be suggested on how to improve the accuracy of the sentiments extracted using existing systems

RQ2: What do modifiers contribute to two-word oxymorons?

In this section, I shall examine how modifiers are used to increase or decrease the affective elements in communication, with a finer focus on the incidence of oxymorons as a result of the use of modifiers. In situations where a modifier is modifying a word that it is in contrast to, an oxymoron occurs, whether it is intentional on the part of the speaker or not. Our studies in this section will be focused on two-word oxymorons like *beautifully ugly, original copy, deeply superficial* and *faithfully unfaithful*.

This section will seek answers to the following sub questions:

a. Is the meaning of a sentence altered when the modifier in the oxymoron is removed?

b. Do the modifiers in two-word oxymorons have inherent sentiment values?
c. What is the significance of the polarity of the modifier in a two-word oxymoron?
d. If oxymorons are isolated, do they present the same affect as when used in sentences? (Does context matter?)

Answers to these will impact computational linguistics in light of methods used for sentiment extraction, be they rule-based or machine learning, and how to enhance the algorithms that are employed in these methods so as to ensure that the polarity of individual words within the oxymorons are brought to bear on the total affect extracted from the oxymorons.

RQ3: What do modifiers contribute to affective metaphoric communication?

Though metaphors are a means of conveying affect, it is also possible to either deepen or lighten the magnitude of the affect conveyed, which is one place where we find the use of modifiers.

Let us consider the metaphor

- *Adam was made to walk the plank.*

The phrase *walk(ing) the plank* alludes to a form of execution used in the 17th century mainly by pirates, whereby a victim was forced to walk off the end of a board (plank) laid on the edge of a ship's deck and jutting out over the sea, so as to drown. In modern days, it is often used when people are being forced to leave their jobs, or take actions that are seemingly detrimental to them, but which actions are considered as the best interest for a larger group. It is used to denote a person suffering punishment at the hands of someone.

The modifier *narrow* can be introduced to make this metaphor read

- *Adam was made to walk the **narrow** plank*

The introduction of *narrow* makes the reader understand that the punishment that Adam was facing had been made even more painful, or crueller. Walking on a piece of wood is difficult enough (literally), but making him walk a narrow piece of wood takes more excruciating effort, even though it is still towards an end in doom.

Another modifier can yet be added to make the metaphor read

- *Adam was made to walk the **long, narrow** plank*

The addition of *long* modifies the narrow plank because literally, when a path is narrow, anyone wishes to pass it quickly. Having to walk a narrow path for a long time paints a picture of a very cruel way that one has to balance one's self so that one can stay alive for as long as possible. The introduction of the modifiers therefore definitely intensifies the emotion of the statement being made in this case.

Let us consider another example:

- *His home was a prison*

This metaphor is describing the state of his home in the light of how a prison is. It therefore paints a certain negative picture because of what a prison looks like in our minds already. If I introduce the modifier dark and rewrite it as

- *His home was a **dark** prison*

I immediately get an even more depressive picture of his home. A prison is already pictured as a small, restrictive and cramped living compartment with iron bars, a small bed with stained white sheets, and walls that invoke a claustrophobic feeling. Removing the light component from such a place intensifies the darkness of the image created.

I can add another modifier to create an even darker emotion

- *His home was a **dark, haunted** prison*

Suddenly, in addition to being restrictive, depressive, dark and very unwelcoming, an element of fear is introduced which further deepens the negativity of the emotions in the image. Our study on this RQ will examine the results that may be achieved by mixing modifiers and metaphors.

The crucial question will be analysing how these are taken care of during a sentiment analysis process.

RQ4: In order for a system to detect affect, is it beneficial for it to detect metaphor and oxymoron?

In this section, I examine how some existing SA systems handle sentiment evaluation on metaphors and oxymoron, this being the crux of the research. The systems being examined include VADER, ItenCheck, Free Sentiment Analyzer, and MonkeyLearn. They will be used to attempt sentiment extraction from metaphoric sentences, and then the results compared with extracted sentiment from the same metaphors but in paraphrased English formats. I will then conclude on whether or not it is imperative that a system which seeks to evaluate discourse be able to identify, even if not to interpret, the incidence of literary devices like metaphors and oxymorons. This will allow us to build a system that takes all the recommendations into consideration on one hand, or modify, improve or enhance the capabilities of existing systems such that their accuracy of extracting correct sentiment is greatly improved.

1.4 Methodology

I will be using as series of empirical studies, each designed to address a particular research question. The general tools that will be used will include the following:

- British National Corpus, which is a 100-million word collection of samples of both written and spoken British English from a wide range of sources, for comparative study of some words and sentences in British English.
- GloWbE, which contains about 1.9 billion words of text from twenty different countries, will be used for text and sentence analysis on different dialects of English.
- WordNet, which is a large lexical database of English text that has nouns, verbs, adjectives and adverbs that have been grouped into sets of cognitive synonyms (synsets), and each of these synsets express a distinct concept.
- SentiWordNet, which is a sentiment-based lexicon derived from the WordNet database, and has each synset being associated with numerical scores to represent their sentiment information. This will help with our computations of sentiment scores.

- Python, which will be the main programming language used to access samples from WordNet and SentiWordNet
- VADER, which is a sentiment analysis tool that can be used as part of the Python programming language to evaluate sentiment in short pieces of text.

1.5 Significance of the Study

This project is about metaphors in discourse, the impact of modifiers on the sentiment evaluations of metaphors, sentiment analysis (SA), and how some existing automated Sentiment Analysis systems cope with literary devices, specifically metaphors and two-word oxymorons. Some issues arising from this research include the inaccuracies of major lexical libraries like SentiWordNet, and how they affect the quality of sentiment extracted from it, a challenge for which I propose using extensive crowdsourcing to enhance the extracted sentiment. I also propose incorporating metaphor and oxymoron-detection tools into existing sentiment analysis systems to enhance systems' ability to identify and evaluate non-literal text before affect detection is carried out.

1.6 Limitations

One major limitation to this study has been the need to continue using WordNet and SentiWordNet for analysis of phrases and extraction of sentiment even though errors were detected in the sentiment representation for some adverbs. This is because there is no other readily available library that has been structured in the way that SWN has been. It was impossible in the amount of time available to construct a new rigorously-tested corpus would be robust enough for the analysis done in this study. The ability to do that would have ensured that I avoided the inherent errors in some of the results of this study.

1.7 Definition of Terms

This section will define the major thematic terms used within the study.

1.7.1 Communication:

Communication is defined by the Macmillan Dictionary as the process of giving information or of making emotions or ideas known to someone, as well as the process of speaking or writing to someone to exchange information or ideas. According to the Oxford Dictionary, it involves the impartation or exchange of information by speaking, writing or using some other medium, as well as the successful conveyance or sharing of ideas and feelings. There are three basic categorizations of communication – verbal, which involves listening to a person to understand their meaning; written, in which a piece of text or a document is read to get the meaning of what is being carried across; and non-verbal, which is inferred by watching for body language like facial expressions, body stance (exclusive of sign language) and tone of voice. The role of language comes into play when communication is either verbal or written. In our everyday lives, languages help us to express our emotions, ideas, aspirations and information, and in generally exploring the world around us by the queries we send out (in the form of questions) and the feedback (answers) that we receive. A combination of words, gestures and tones are used in varying degrees to help portray a wide spectrum of emotions.

1.7.2 Metaphors

There is a traditional, naïve view that metaphors are supposed to be something that is a prerogative of the creative arts including poets and the performing artistes. The Oxford Reference (oxfordreference.com) defines 'metaphor' as a figure of speech in which a word or phrase is applied to something to which it is not literally applicable (e.g. food for thought). Another meaning is 'a thing symbolic of something else'. In much simpler terms, this means using one thing to describe another thing and implies that metaphors are representations, and as such, do represent ideas but are not in themselves the idea. In other words, a metaphor is an expression that refers to something that it does not literally denote, in order to suggest a similarity. All of us, every day, speak, write, and think in metaphors. In fact, it is hard to imagine how we would get by without them. George Lakoff (1992) states, "*metaphor [is] not a figure of speech, but a mode of thought defined by a systematic mapping from a source to a target domain*". There is a claim that metaphor is not primarily a matter of language, but structures in thought and action (Ortony, 1993; Lakoff and Johnson, 1980), and the over-arching answer lies within cognitive sciences, and more specifically, cognitive linguistics, which shows that language interacts with the perception, memory and reasoning of a person. The essence of metaphor is to understand and to experience one kind of thing in terms of another, or to see something in terms of something else (Lakoff and Johnson, 1980; Burke, 1969). The purpose of metaphors is basically twofold: (1) its referential purpose is to describe a mental process or state, a concept, a person, an object, a quality or an action more comprehensively and concisely than is possible in literal or physical language; (2) its pragmatic purpose, which is simultaneous, is to appeal to the senses, to interest, to clarify graphically, to please, to delight and to surprise. The first purpose is cognitive, the second affective. In a good metaphor, the two purposes fuse (and are parallel with) content and form; the referential purpose is likely to dominate in a textbook, the aesthetic often reinforced by sound-effect in an advertisement or popular journalism (Newmark, 1988). Some examples of metaphors include:

- *Do not put all your eggs in one basket.*
- *It is raining cats and dogs!*
- *Never look a gift horse in the mouth*

Some metaphors from literature include:

- *I am the good shepherd...and I lay down my life for the sheep.* – Jesus of Nazareth (Dake, 2004).
- *All the world's a stage, and all the men and women merely players.* (Bromley et al, 1799)
- *The public are swine, advertising is the rattling of a stick inside a swill-bucket.* - George Orwell (Orwell, 1956)

1.7.3 Affect

Affect (noun) originates from a 19th century German word which was coined from Latin *affectus* meaning 'disposition', and also *afficere* meaning 'to influence'. The Oxford Dictionary explains *affect* as 'emotion or desire as influencing behaviour'. An example of the use of *affect* in a sentence is

- *This, says Jung, is because they confuse feeling with emotion or affect.* (Stevens, 2001)

Affect, as used in psychology (Hogg, 2010), is the experience of feeling or emotion, and can refer to a facial, vocal or gestural behaviour that serves as an indicator of affect (APA, 2006). For the purposes of this project, I shall assume that synonyms of affect include *emotion*, *sentiment* and *attitude*, and these words may be used interchangeably.

1.7.4 Modifiers

Modifiers, according to the Oxford Learner's Dictionaries, are words such as adjectives or adverbs, which describe other words or group of words, or restrict their meanings in some way. It is from a Latin word which means 'to attribute a quality to'. Modifiers, sometimes called qualifiers, are words or phrases (usually adjectives or adverbs) that precede or succeed other words (like nouns, verbs, adjectives or adverbs), and in some cases, aim at qualifying the meaning of those words by increasing or decreasing the quality signified by the words they modify. In some other cases, they could denote a state (*Charles is unruly*) or a time (e.g., for an event – *The high ball is at 5pm*). Some common modifiers in English include *very, quite, rather, somewhat, more, most, less,* *least, too, so, just, enough, indeed, still, almost, fairly, really, pretty, even, a bit, a little, a (whole) lot, a good deal, kind of* and *sort of.* Examples of sentences containing modifiers include:

- *He found the water quite cold.*
- *Suzzy is pretty lazy about school.*
- *There is a fairly spectacular waterfall in the Kwahu mountains.*
- *James has a reputation among the teachers for being kind of grumpy.*
- *Miriam is a good deal smarter than your average undergrad.*

For a word like *fairly*, its usage as a modifier indicates an almost large or reasonable degree of quality. In our opinion, it is used more easily with favourable and neutral adjectives, rather than with strongly unfavourable ones, for examples, *fairly intelligent, fairly satisfied, fairly reasonable*, but not *fairly dishonest, fairly foolish,* or *fairly unreasonable.* There are a number of modifiers that also suggest that something is very close to having the attribute that is named. These include *almost, nearly, roughly, approximately, partly* and *largely* (Downing, 2014). Examples of the usage of these modifiers include:

- *He **almost** made it to the concert on time*

This means he was much closer to making it on time for the concert, than he was not. The sentence is however ambiguous since we do not know whether or not he made it to the concert at all.

- *Sally **nearly** missed her train*

This suggests that Sally didn't miss her train but rather, she made it with very little time (relative to the time the train was departing) to spare. Another way to say this same sentence would be *Sally almost missed her train*, and it would have the same meaning and affect.

- *Adam has **largely** finished the work*

This presupposes that Adam hasn't finished the work yet, but on a spectrum of not-started to completely-finished, he is closer to finishing. Another modifier that could be used would be *almost*.

1.7.5 Oxymorons

An oxymoron is a figure of speech that the Merriam-Webster Dictionary defines as a combination of contradictory or incongruous words. Examples include *living dead*, *deafening silence, bitter sweet, alone together* and *original copy*. In some cases, the contrasting words or phrases do not always appear together. They could be spaced out in a sentence, with examples including *In order to lead, you must walk behind.* Oxymorons can add more colour, humour and meaning to language in many different ways. They are also a useful tool that enables a speaker or writer to describe complex and conflicting emotions. They could also be used to create a bit of drama, and have the ability to cause a hearer or reader to pause and consider whether what has been said is one to laugh or wonder about.

1.8 Organisation of the Study

In the next chapter (Chapter Two), which is a literature review, I present and discuss the different types of metaphors, the ways in which they are used and the differences in imagery they create. I will also examine the general uses of modifiers as used in the English language, how they affect the words they modify, how they are used in metaphors to enhance discourse, and how they affect the resulting emotions when used. I will then examine how existing metaphor/affect systems deal with modifiers by reviewing literature on such systems.

In Chapter Three, I will present an outline of the overall methodology, showing the various methodological tools that will be used in the various empirical studies that will be carried out.

In Chapter Four, I will present detailed descriptions of methodologies used in all empirical studies carried out. The results are presented in the form of answers to sub-questions that arise from the research questions. This chapter has been presented in five distinct sections – an introductory section and four other sections, each devoted to an empirical study that is aimed at answering one of the research questions.

In Chapter Five, I will present a summary of the whole report, further discussion on all work done, and come out with recommendations for future research.

1.9 Chapter Summary

In this chapter, I have given a background to the whole study and explained the reasons why this study is important. I have stated the problem statement and explained in detail the research questions that will be answered in order to complete the study. I have stated the limitations to the study and defined the major terms that will be referenced throughout the project. I have also outlined how the study will be organised.

CHAPTER TWO

LITERATURE REVIEW AND THEORETICAL ANALYSIS

2.1 Introduction

In this thesis, I consider the process of detecting metaphors that convey affect, considering the effect of embedded modifiers, and how they impact interpretation. I also attempt to evaluate the sentiment in oxymorons, taking into consideration the role of adverbs, whether or not they have inherent sentiment values, and the effect they have in two-word oxymorons. The literature review of this research has been formed through an in-depth review of relevant books, journals, related theses, conference proceedings and workshops in computational linguistics with a special emphasis on metaphor processing and sentiment analysis. Various methodologies have been outlined within this review with examples of how they have been applied, detailing their drawbacks and leading to the subsequent sections of this research. This chapter will discuss the various components of this research under three main themes: **metaphors**, examining simple and conceptual metaphors and the sentiment that can be derived from them generally, and also when modifiers are added; **affect**, noting that the term affect is used loosely to imply sentiment and to generally cover terms like sentiment analysis, textual polarity, emotion, attitude and semantic orientation to mention a few; and **modifiers** with a finer focus on how they impact communication, adverbs and their roles in sentences, and the incidence of oxymorons. I will also discuss the various types of metaphors and introduce the general principles for affect-detection so as to provide a good background for the concepts used in this Thesis.

2.2 Metaphors

According to the Chambers Dictionary, Metaphor comes from the Greek word *metaphorā* which is itself from *meta* and *pherein*, and which means, "to transfer". The Random House Dictionary of the English Language (Dictionary, 1966) also describes a metaphor as the application of a word or phrase to an object or concept that it does not literally denote, in order to suggest comparison with another object or concept. In much simpler terms, this means using one thing to describe another thing.

Over the last several years, research has revealed that indeed, metaphors and their usage are not just a matter of poetry or literary writing, and neither are they just matters of intellect and academic prowess. On the contrary, they are part of ingrained conceptual systems of which we may not even be aware of, but which govern our thoughts on everything including everyday tasks. It is so much a part of our everyday living and communication that a large number of phrases have lost their classification as being metaphorical, though they are. An example is *mother nature* which, though being clearly metaphorical, may not appear in anyone's list of metaphors as it is now largely considered as a cliché. This seemingly seamless incorporation into our everyday lives, has also given rise to many new categorizations of metaphors, including the new ones that writers invent during discourse, which then become novel metaphors, and which, with very frequent use, may end up in the category of those that are considered more as clichés than metaphoric.

Lakoff and Johnson first articulated the systematic analysis of metaphor in their work *Metaphors we live by* (Lakoff and Johnson, 1980), which they referred to as the Conceptual Metaphor Theory, and in summary, explained that "the essence of metaphor is understanding and experiencing one kind of thing in terms of another". Their work set the tone for much research, especially in cognitive science within the metaphor domain, and this has remained the case to date. The idea is to understand a complex or abstract idea through an intermediary, more concrete idea. The use of metaphor has so permeated language and speech, that they are used without paying much attention to them. They have ceased to become the preserve for poetry and the fine arts, and a lot of metaphorical phrases are considered as part of everyday language in everyday life. Examples of common phrases (a selection from Kövecses, 2002) include

He's without direction in life.

I'm where I want to be in life.

I'm at a crossroads in my life.

She'll go places in life.

He's never let anyone get in his way.

She's gone through a lot in life.

In their work, *Metaphors we live by*, Lakoff and Johnson put together an organized set of metaphorical data which they claimed reflected structures in the human cognition. The following are some examples (1980, p.47, italics in original) to this effect, and Lakoff and Johnson claim that these examples draw on people:

- The theory of relativity *gave birth* to an enormous number of ideas in physics.
- He is the *father* of modern biology.

- Whose *brainchild* was that?
- Cognitive psychology is still in its *infancy*.
- That's an idea that ought to be *resurrected*.
- Where'd you *dig up* that idea?
- He *breathed new life into* that idea.

Even though their work set the tone for further research, it was also heavily criticized (Murphy, 1996, 1997; Steen 1994) especially on the sets of examples they used, with one such criticism being that the example sets were created by the writers rather than collected from language as used by ordinary people in ordinary everyday life. Another criticism involved examples like

- Look at what his ideas have *spawned*

Spawned is used here to mean an idea that has been ***birthed,*** as if to say only people have the ability to give birth. *Spawned* however is used primarily on fish, frogs, molluscs, crustaceans, etc., and rather often used in a derogatory manner when used on persons. Other such questioned examples include

- Those ideas *died off* in the Middle Ages.
- His ideas will *live on* forever.

where they implied that *died off* and *live on* can be applied to other living creatures including plants, and not just people (metaphorically) and ideas (referentially). Lakoff and Johnson concluded that metaphor is not just a matter of language made up of mere words, but that human thought processes are largely metaphorical.

2.2.1 Metaphor Identification

On the issue of metaphor identification, both Lakoff (1986, 1993) and Gibbs (1993, 1994) have concluded that identifying metaphors in discourse could be a case of looking for the indirect meaning in words or phrases used. When a statement is made that *Linda is an angel*, it does not refer to the literal sense of an angelic being, but the attributes of that spiritual entity, being superimposed on Linda who is human. In Macmillan's Advanced dictionary, which is based on corpus research, the first meaning of ***angel*** is *a spirit that in some religions is believed to live in heaven with God. In pictures, angels are shown as people with wings*. The second meaning has been tagged as "*mainly spoken*" and means *a very kind person*. In this sense, the metaphorical meaning has been so widely used and accepted that it has been conventionalized and added to the official definition in the dictionary. This conventionalism does not however negate the word ***angel*** from being used metaphorically or otherwise. The meaning, whether literal or inferred, may be obtained more accurately by considering the context within which it is used.

Even though there is a lot of research done in the area of metaphors and its associated properties in discourse, there doesn't seem to be a universally agreed-upon categorization of metaphors, as well as a standard criterion for identification. There is therefore a great probability of different people picking out different metaphors from a given text. Because initiators of discourse can create their own metaphors, the import of novel metaphors may be lost on the ordinary listener. The complexity of identifying metaphors is made even more prominent by the individual differences in metaphor identification. Individuals in this sense include the Pragglejaz analysts who analysed a large amount of data including nineteenth century poems for metaphorically-used words. The word "Pragglejaz" was coined from the initials of the first names of the analysts: **P**eter Crisp (HK), **R**ay Gibbs (Berkeley), **A**lan Cienki (VU), **G**raham Low (York), **G**erard Steen (VU), **L**ynne Cameron (Open Univ), **E**lena Semino (Lancaster), **J**oe Grady (primary metaphors- Berkeley), **A**lice Deignan (Leeds) and **Z**oltan Kövecses (Hungary). They collaborated for six years in an attempt to develop a tool for metaphor identification that is both reliable and valid in terms of statistical tests and cognitive linguistics, a tool they named as the Metaphor Identification Procedure (MIP). They published their procedure as Pragglejaz Group (2007 cf. Steen, 2002), and in this publication, outlined the ways in which the MIP could be used by metaphor researchers to carry our different empirical research. They noted how the differing intuitive orientations of various researchers affect their perceptions on what word is or is not metaphorically used. This presents a great difficulty in comparing different empirical analyses, thereby complicating any evaluations of theoretical claims about the frequency of metaphor, its organization in discourse, and the possible relations that may exist between metaphoric language and metaphoric thought (Cameron, 2003; Semino, Heyword and Short, 2004). One of the popular definitions of what a metaphor is, is what Lakoff and Johnson (1980) termed as the Conceptual Metaphor Theory, which entails understanding one idea or conceptual domain, in terms of another. For the purposes of this research, I will restrict the categories of metaphors to be discussed at all stages to conceptual metaphors as well as other ranges of expressions that are not clearly conceptual, relying on the ad hoc transfers of properties.

2.2.1.1 Conceptual Metaphors

The term *conceptual metaphor* was introduced in *Metaphors we live by* (Lakoff and Johnson, 1980). Basic conceptual metaphors are part of the common conceptual apparatus shared by members of a culture. They provide a specified framework within which there could be a wide variety of links between the source and target structures, thereby allowing many utterances to rest on that conceptual metaphor. We usually understand them in terms of common experiences, and they are largely unconscious, though attention may be drawn to them. According to Lakoff (1987, 1993), Johnson (1987) and Turner (Lakoff and Turner, 1989), experiences are represented by structured and coherent patterns, and so to make them clearer for the purposes of comprehension, concepts that are simpler or clearer in structure are employed. Abstract experiences are better understood by employing structural patterns unto simpler experiences. Conceptual Metaphors can also be seen as a sort of mental picture from which concepts are constructed. Their operation in cognition is almost automatic. They are widely conventionalized in language, that is, there are a great number of words and idiomatic expressions in our language whose meanings depend upon those conceptual metaphors (Lakoff and Turner, 1989). It is also entirely possible for novel metaphors to exploit the conceptual metaphor theory. Lakoff and Johnson (1980, pages 8,9) mention some metaphorical phrases, which are often referred to as linguistic metaphors, which use the structure of ***TIME IS MONEY***:

- You're *wasting* my time.
- This gadget will *save* you hours.
- I don't *have* the time to *give* to you.
- How do you *spend* your time these days?
- That flat tire *cost* me an hour.
- I've *invested* a lot of time in her.
- You're *running out* of time.
- Is that *worth your while*?
- He's living on *borrowed* time.

It is worth noting that even though Lakoff and Johnson (1980) list these metaphors under the TIME IS MONEY concept, several of the examples do not evidently mention money specifically, but rather any resource that might run out, be saved, wasted, etc., for example, many things can be borrowed and not just money.

2.2.1.2 Other Metaphors

Based on the meaning of what a metaphor is according to the Oxford dictionary, I will define a metaphor as something that has been used as symbolic of another thing to which it literally does not denote, allowing the vehicle (the object whose attributes are borrowed) to directly transfer its meaning to the tenor (the subject to which attributes are ascribed). Metaphors in this case, will include the following examples:

- *Eleanor's tears were a river flowing down her cheeks.*

A river is a large natural stream of water that flows out in a channel into another river, a lake or even the sea, and is so much larger than any amount of tears a person can shed. Ascribing the attributes of a river to tears is a creative way of saying that Eleanor cried a whole lot, and that the tears were so much that it reminded the writer of a river and how it flows. Another example can be

- *Rita is a peacock.*

A peacock is a very attractive bird that has a large colourful tail when in full plumage, and so ascribing the attributes of a peacock to Rita gives the idea that Rita is a beauty. Yet another example is

- *The Lord is my rock.*

There are several places in the Bible where rock has been used including water coming out of the rock (Deut. 8:15) and God hiding Moses in the cleft of the rock (Ex 33:22), and so *rock* is equated with strength, provision, shelter, fortress, hiding place, as well as being solid. All these attributes therefore get ascribed to *The Lord*, and have nothing to do with Him being a physical rock. Another example

- *George is a lion*

ascribes the attributes of the lion which include bravery, fierceness, strength, courage and kingship, to George, and does not mean that George is literally an animal, or that there is a lion named George.

2.2.1.3 Other classifications of metaphors

As a follow on from the earlier stated observation that there exists many different categorisations of metaphors, the following classifications have been included here just to buttress the point of subjectivity. Different linguists have categorized metaphors in different ways. Aristotle (1991) differentiated between simple or double metaphors, current or strange metaphors, and common or unused metaphors. Broeck (1981) categorised metaphors into lexicalized (referring to lexical units that have lost their metaphoric edge and have become part of normal lexical entities in a given language), conventional (referring to a fixed and common metaphor which the language users easily recognize), and private (referring to the innovations of individual persons). Black (1962) proposed that metaphors are either dead or alive, and added that a metaphor could also be said to be dormant if its metaphoricity is normally not apparent, but can be enlivened; active if it is novel; strong if it has a high emphasis; and weak if it has a low emphasis.

Considering the various categorizations, Newmark's classification (Newmark, 1988) appears to be a bit more comprehensive and is outlined as follows:

1. Dead Metaphor – This is a metaphor that has lost its figurative and connotative meanings, and is used like any ordinary words in the language. Its metaphoric image gets lost on both the speaker and listener, and these include some concepts of space and time, as well as the usage of some main body parts (Tajali, 2003). Examples include

- *At the foot of the hill*

- *The arm of the chair.*
- *As a matter of life and death*

2. Cliché Metaphor – Very much like the dead metaphors, they have been used so much so that they cease to convey any figurative meaning, and become a good way of summarising common experiences and situations in a particularly effective way. Examples of this would be

- *This whole exercise has been a complete waste of time.*
- *He's a rat.*
- *Mother nature*

There doesn't seem to be much of a difference between the dead metaphors and the cliché metaphors, as defined by Newmark, since both show a fundamental concept of metaphors that seem to have lost their appearance as metaphors because they are so commonly used in everyday language by people who may not intend using metaphors.

3. Stock or Standard Metaphor – This, Newmark (1988) describes as 'an established metaphor which is in an informal context and is an efficient and concise method of covering a physical and/or mental situation both referentially and pragmatically', Stock metaphor have not been deadened by overuse, and its examples include

- *Earn a living*
- *Keep the pot boiling*
- *Keep something going*

4. Recent Metaphor – These are often contemporary phrases in modern language that have been coined from actions, things or qualities that continually 'renew' themselves in discourse with examples being

- *Spasmoid* to refer to stupid (though it actually means 'related to a spasm')
- *pissed* to refer to drunk (but which means to be very annoyed in Northern America)

5. Original Metaphors – Metaphors that are invented by a writer and become a source of enrichment for the target language. These will be metaphors whose first usage is in the first copy of the document or conversation they are appearing in. It must be noted that every metaphor will go through the original metaphor stage before they come into mainstream use. An example can be taken from The Bible (John 10:11, KJV):

- *I am the good shepherd: the good shepherd giveth his life for the sheep.*

2.2.2 The MIP and the MIPVU

It is important to reliably and systematically identify metaphors before attempting to analyse them. Two broad ways in which metaphors can be identified are first, starting from the conceptual metaphor and then tracing downwards for expressions that are compatible with that mapping (e.g. Koller, 2004) and second, searching for words that are used metaphorically and then tackling them bottom-up without the presumption of any conceptual metaphor

(Pragglejaz Group, 2007). Analysing metaphors can therefore be approached in two ways – as a system of language or as a system of thought (Steen, 2009).

For the purposes of a comprehensive metaphor identification and analysis, because the list of conceptual metaphors can be very large and there are no clear cut-off points, it may become increasingly difficult, and so some metaphors may not be identified as such. Cameron (2003) rightly concludes that once a conceptual metaphor is presumed, the evidence found would be only that which we are looking to find, and so metaphors that fall outside that concept may be missed. This aside, the bottom-up fashion for metaphor identification may also prove to be porous and riddled with inconsistencies if not carefully handled. It may be so much easier for analysts to rely on their intuition and foreknowledge of what a metaphor is, and so introduces a large percentage of subjectivity. This subjectivity gives rise to the need for using processes like sentiment analysis and crowdsourcing (a form of opinion mining) where opinions from many different people are collected and analysed for agreement of opinions.

2.2.2.1 MIP

The Pragglejaz group (2007) came up with the Metaphor Identification Procedure (MIP), which seems to be a long and slow process, but gives an 80% accuracy. The MIP places an emphasis on metaphor usage in language and how to identify words that have been used metaphorically in specific pieces of discourse. They base their argument on a simple test which classes a word as metaphorical if its most basic, physical or concrete sense is different and in contrast to its meaning or usage in the piece of discourse being analysed, and if this contrast results in a meaningful comparison between them. In later years, a variant of the MIP which was developed by Steen et al (2010a and 2010b) in Vrije Universiteit in Amsterdam, the MIPVU, also focused on linguistic expressions and their metaphorical potential, and identifies metaphor-related words based on a comparison between their basic and contextual senses of expression. The MIPVU allows researchers achieve a higher reliability (89% accuracy as opposed to 80% for MIP) in annotating metaphoric words because it takes into consideration other complex forms of metaphor use like similes (Steen et al. 2010b: 789). The main tool used for checking contextual and basic meanings of lexical units is the Macmillan Dictionary because it has the Metaphor Boxes feature which explains how familiar words combine to have metaphorical meanings. The Longman Dictionary of Contemporary English was used as a second opinion for cases that were not straightforward using Macmillan alone. The MIP guidelines (as set out in the paper of Pragglejaz Group, 2007) are as follows:

1. Read the entire text–discourse to establish a general understanding of the meaning.

2. Determine the lexical units (a single word or a part of a word that form the basic elements of a language's lexicon or vocabulary) in the text–discourse

3. (a) For each lexical unit in the text, establish its meaning in context, that is, how it applies to an entity, relation, or attribute in the situation evoked by the text (contextual meaning). Consider what comes before and after the lexical unit.

(b) For each lexical unit, determine if it has a more basic contemporary meaning in other contexts than the one in the given context. For our purposes, basic meanings tend to be

—More concrete [what they evoke is easier to imagine, see, hear, feel, smell, and taste];

—related to bodily action;

—More precise (as opposed to vague);

—Historically older;

Basic meanings are not necessarily the most frequent meanings of the lexical unit.

(c) If the lexical unit has a more basic current–contemporary meaning in other contexts than the given context, decide whether the contextual meaning contrasts with the basic meaning but can be understood in comparison with it.

4. If yes, mark the lexical unit as metaphorical.

The procedure was subjected to various tests by six independent analysts to two pieces of discourse, one being words from a news text, and the other being conversations from the British National Corpus. There was unanimous agreement that 4% of the words in the conversation and 7% of the words in the news text were metaphorical. In total, the analysts working independently achieved unanimity on 89% of the words in the conversation and 82% of the words in the news text. If the criteria for measuring the success of the MIP is opened up to include results from 5 analysts instead of the strict six, the percentages rise to 93.1% and 91.1% respectively. The MIP reasons that metaphorical meaning in usage is indirect meaning, and this is seen in the contrast that exists between the contextual meaning of a particular lexical unit, and its more basic meaning, with the basic meaning being absent from the actual context, but then being observable in other contexts. For example, when a word like *attack* is used in the context of an argument, its meaning in context will be in relation to a verbal exchange as opposed to its basic meaning which denotes a physical engagement between two persons (Lakoff 1986, 1993; Gibbs, 1994). Because the basic meaning gives a mapping to the contextual meaning on the premise of some kind of nonliteral comparison, all uses of *attack* in the contexts of arguments can be correctly analysed as metaphorical. The MIP works well in identifying both conventional and novel metaphors by allowing contextual senses to be compared with and contrasted to the basic senses, and so allows an operational way of identifying all indirectly used metaphors in discourse. The MIP, as an advantage, allows an easy accommodation of a researcher's standards, as contextual meanings, whether conventional or novel, are compared with meanings as outlined in the Macmillan Dictionary in order to tackle social differences in metaphor usage by way of providing a standardized general lexicon. MIP also limits the analysis of metaphor to the level of words or lexical units.

2.2.2.2 MIPVU

The MIP was expanded into the MIPVU (Steen et al., 2010a; Steen et al., 2010b), with one of the main modifications being a precise definition on what constitutes a 'lexical unit', especially because of multi-word units including phrasal verbs like *break down*, compound nouns like *United*

Kingdom, and polywords like *of course*. In the case of phrasal verbs (like *break down* in *The ability to break down a problem is an essential trait for successful problem-solving*), the combination of the verb and the particle refer to a single action, as well as activating one concept, and this action is therefore categorized as one lexical unit. With the compound nouns (like *United Kingdom* as in *The United Kingdom consists of Scotland, Wales and England*), it also refers to a single and specific entity. These compound words are however not problematic in analysis if they are hyphenated (as in *six-pack*). Again, polywords (like *of course*) also denote one referent, and since not all of them are listed in the dictionary, they used a finite list that has been published as part of the British National Corpus (BNC, www.natcorp.ox.ac.uk) to aid in annotation. The MIPVU also includes the possibility of including other types of metaphors such as simile (which is directly expressed in language as in the case of *He is like a pig* where *pig* becomes the source domain in a cross-domain mapping, and the expression is a form of an explicit comparison), and implied metaphors (which are identified by substitution or the use of ellipsis), and considers metaphors from the level of conceptual structures (Steen 2007). Again, the MIPVU adopts a word class level (a category of words of similar form or functions; a part of speech, like noun, adverb, adjectives, verb) approach in identifying contextual and basic meanings, as opposed to the MIP which uses a lemma level (base words and their inflections, or the head words in a dictionary; e.g., *run* is a lemma while *run, runs* and *running* are different forms of it) basis for identifying lexical units. It also makes a distinction between transitive, intransitive and linking verbs, as well as count and uncount nouns.

The steps of MIPVU (Steen et al., 2010a:25-26) are as follows (with brief explanations on how the steps can be achieved):

1. Find metaphor-related words (MRWs) by examining the text on a word-by-word basis.

In order to achieve this, words are considered as separate lexical units if they have individual Part-Of-Speech (POS) tags, and all polywords also considered as single lexical units.

2. When a word is used indirectly and that use may potentially be explained by some form of cross-domain mapping from a more basic meaning of that word, mark the word as metaphorically used (MRW: indirect)

For this purpose, the contextual meaning of the lexical unit must be identified, and it should be checked for a more basic meaning. Then, determine if there is a sufficient distinction between the more basic meaning and the contextual meaning, then examine whether or not the contextual meaning can be related to the more basic meaning by some similarity.

3. When a word is used directly and its use may potentially be explained by some form of cross-domain mapping to a more basic referent or topic in the text, mark the word as direct metaphor (MRW: direct).

Lexical units which are used directly and are related to metaphors can be identified by finding a local referent and associated topic shifts (Cameron 2003; Charteris-Black, 2004), testing if the lexical units are supposed to be integrated into an overall referential and/or topical framework by some means of comparison (Goatly 1997), testing whether \ the comparison is non-literal or cross-domain (Cameron 2003), and then testing whether or not the comparison can be regarded as a form of indirect discourse about the main topic of the text.

4. When words are used for the purpose of lexico-grammatical substitution, such as third person personal pronouns, or when ellipsis occurs where words may be seen as missing, as in some forms of co-ordination, and when a direct or indirect meaning is conveyed by those substitutions or ellipses that may potentially be explained by some form of cross-domain mapping from a more basic meaning, referent, or topic, insert a code for implicit metaphor (MRW: implicit).

Implicit metaphors arise in two forms – by substitution (Halliday and Hasan, 1976) and works by pro-forms such as pronouns; and by ellipsis which works through unrealised words that may be inserted into grammatical spaces or gaps.

5. When a word functions as a signal that a cross-domain mapping may be at play, mark it as a metaphor flag (MFlag)

A lexical signal alerts the language user to the fact that a contrast or comparison of some form is at play, and so simple markers for simile (including *like, as, more, less, more/less ... than, regard as, conceive of, imagine, think, behave as if*) are coded as MFlags. More general signals of indirectness (including *sort of, kind of*) were excluded, as well as what Goatly (1997) termed as topic domain signalling like the use of *intellectual* in *intellectual stagnation*.

6. When a word is a new-formation coined by the author, examine the distinct words that are its independent parts according to steps 2 through 5.

metaphor is taken, and the other being the target domain of the surrounding context within which the metaphor is to be interpreted.

Long before annotated corpora became accessible, it was acceptable that a sufficient criterion for metaphor detection was the violation of a semantic preference of a verb or adjective (Wilks, 1978), and so another key attribute of metaphors, according to Wilks (1978) is selectional preferences in semantics. In this theory, verbs constrain their syntactic arguments by the semantic concepts they accept in these positions, a constraint that metaphors violate by combining incompatible concepts. As an example, the verb *drink* has a preference for liquid and animate objects, making *My SUV drinks so much gasoline!* violate its subject preference, which then becomes a clue to the possibility of it being metaphorical. Early work in this regard largely depended on intuition and sometimes, salience. Later, researchers like Resnik (1997) worked on deriving preferences using available corpora. The semantic preferences in VerbNet remained largely intuitive in its origins. Preference violation was linked to metaphor detection by Fass and Wilks (1983) and Martin (1990), and both were based on work done with hand-crafted resources. Dolan (1995) however proposed that there were implications of using large-scale lexical resources, and so Peters and Wilks (2003) used WordNet in conjunction with corpora.

Constructing an automated system to detect metaphors will require extensive knowledge about both the conceptual mappings and the preferences, which leads a lot of researchers into aiming for high precision for specific mappings instead of attempting to provide a system that has a wide general coverage. Even this is a daunting task because, limiting automated detection to one domain requires knowledge of many metaphoric source domains in order to cover all possible mappings, and these mappings themselves must be known.

A number of approaches (Gedigian et al., 2006; Krishnakumaran and Zhu, 2007; Mohler et al., 2013; Tsvetkov et al., 2013) have made use of manually constructed knowledge bases like WordNet and FrameNet to establish the conceptual domains. Others like Shutova et al (2010) and Heintz et al (2013) have made use of topic modelling whereby topics are identified to best describe a set of documents. Strzalkowski et al. (2013) used ad-hoc clustering while Hovy et al. (2013) used semantic similarity vectors.

Mason's CorMet program (2004) has attempted to identify conceptual metaphors for verbs. It does this by drawing knowledge from WordNet and using that to select preferences for different domains. For example, the object of the verb *cook* is usually food, so when *cook* occurs in a text on ideas, the program would infer a metaphorical mapping from IDEA to FOOD. CorMet has however been judged as being too subjective since it achieved only 77% accuracy on a sample of 13 mappings, and it is eventually the analyst who is supposed to judge whether or not the output corresponds with the master metaphor list.

Berber Sardinha's Metaphor Candidate Identifier (Sardinha, 2010) is an online tool that attempts to identify words that have been used metaphorically in text. It uses knowledge from training data amassed from 23,000 hand-coded words using MIP. The program works by matching each word from a text, its pattern and its part of speech, and calculates an average probability of it being used metaphorically in that text.

Schulder and Hovy (2014) proposed a system that utilizes a statistical approach to detecting metaphor, and uses the rarity of novel metaphors by determining words that typically do not match a metaphor vocabulary. Their system does not require a foreknowledge of semantic concepts of the metaphor's source domain. They measure just how "out of place" a word is in a given context, with the hypothesis that a word that is out of place signifies a word that is not meant literally, but rather, metaphorically. They made use of a domain-specific term relevance metric which consisted of two main features: domain relevance which evaluates whether or not a term is typical in the context of the literal target domain and is based on the term frequency inverse document frequency (TF-IDF), and common relevance which shows the terms that are so commonly used across the various domains such that they have no discriminative power. A piece of text that proves to not be typical for that domain, and is also not common enough, is considered a metaphor candidate. One advantage of their system is that it only requires knowledge about the text's literal target domain, which helps in making it noise-proof, thereby allowing the use of large, uncurated corpora. Their system was analysed as a stand-alone classifier which reported a performance measure of between 58% and 68% accuracy, noting that it worked better when data was sparse, as opposed to diminished accuracy as training data increased.

Wilks et al., (2013) used an experimental algorithm to detect implicit conventional metaphors in the lexical data of a resource like WordNet with an emphasis on metaphors that would otherwise never be detected by other algorithms since they are coded into the senses and so would never violate any preferences as their constraints are always satisfied by such senses. They first implemented their algorithm in VerbNet, and then constructed a more detailed set of constraints based on WordNet glosses. They proposed that their algorithm could help significantly improve the performance of existing metaphor detection algorithms that do not attempt to identify conventional metaphors. This is mainly due to the use of WordNet-derived data that contains adjective constraints unlike other lexical resources. They based the algorithm development on the fact that conventionalised metaphors are already encoded into lexical resources, with a typical example being *Tom is a brick* which has been encoded as a sense of brick in WordNet (Miller, 1995). They then used a simple method to extract all such conventionalised metaphors into a candidate pool even in the instances in which they are not indicated. They proposed that if a word whose main sense (usually the first sense) in WordNet fails the main preference for the sentence slot it fills, or happens to have a lower and less frequent sense that satisfies that preference, then the lower sense can be said to be a metaphorical sense. In the case of a sentence like *Harry is a pig*, the main sense of a pig is AN ANIMAL, which clearly fails in equating Harry because Harry cannot be a human being and an animal. Yet, the third sense has a definition as "a person who is regarded as greedy". In this case, *Harry is a pig* can be possibly metaphoric in meaning. This hypothesis is however not based on any assumption of strict ordering of the WordNet senses. For their experiments, they made use of WordNet, VerbNet and the Stanford parser (de

Marneffe et al., 2006) which Finkel et al. (2005) names as the Entity Recognizer, with the recognizer preplacing sequences of text representing names with WordNet senses which have hypernyms that exist in the selectional restriction hierarchy. The preferences that they derived from WordNet definitions helped them to replace VerbNet with a new lexical resource that both reduced the complexity involved in finding the preference violations, as well as improving performance, which helped greatly with good recall.

Shlomo and Last (2014) used a supervised learning approach which they called MIL (Metaphor Identification by Learning), in which they made use of a set of statistical features derived from a corpus that represents a specific domain (e.g., news articles published by Metro). They used it to identify three major types of metaphoric expressions without using any knowledge bases or handcrafted rules. They also made use of an annotated set of sentences that had been labelled by native English speakers as metaphoric or otherwise, and then induced a metaphor identification model for each expression by using a classification algorithm to the set of annotated expressions.

The three major types of syntactic structures used were based on the work of Krishnakumaran and Zhu (2007) and these are as follows:

Type 1 – A noun (subject) related to another noun (object) by a form of the verb 'to be', as in the example *I am the good shepherd.*

Type 2 – A noun (subject) associated with a metaphorically used verb and another noun (object), as in the example *The memory lurked in a dark corner of his mind.*

Type 3 – An adjective-noun phrase as in the example *sweet tooth.*

Since an example of each of these types may or may not be metaphorical in essence, the expressions were labelled as such, and the entire metaphor identification problem was evaluated as a binary classification problem.

In related works, Birke and Sarkar (2006) majored on classifying the use of the verbs in a given sentence as either literal or non-literal, which is essentially the type 2 structure, and adopted the work of Karov and Edelman (1998) who focused on word sense disambiguation of words within specified contexts like sentences. Neuman, et al. (2013) also outlined three rule-based algorithms for identifying metaphors, and suggested identification by negating literalness, using a rule-set that is built upon multiple knowledge resources like Wiktionary and WordNet. Shutova et al. (2010) outlined a semi-supervised learning procedure for identifying the type of metaphors that use verbs in metaphorical manners (type 2), using the principle of clustering by association. This principle uses the verb's subject as an anchor in identifying the words that are in the neighbourhood of the verb. Turney et al. (2011) used logistic regression to implement a metaphor identification solution which they called the Concrete-Abstract algorithm, and which they used to help identify metaphors that are adjective-noun phrases (type 3). They suggested using the abstractness level of words in a given expression as opposed to using Word Sense Disambiguation, and they reasoned that this would be a better solution since a wide range of nouns in the type 3 metaphoric expressions are abstract while their adjectives appear to be concrete. The main limitation of their model was it using only one feature to cover a myriad of expressions. Shlomo and Last (2014) extended the single feature set used by Turney et al. (2011) by a large number of statistical features, which resulted in a significantly improved model. The rule-based algorithm, CCO of Neuman et al (2013), however outperformed Shlomo and Last's (2014) MIL because it applied a set of rules to an expression with the aim of determining whether or not it is literal, with these rules being separately generated for each of the three types of expressions. Even though CCO outperformed MIL by about 20%, it exhibits the huge disadvantage of having to use large amounts of linguistic resources which becomes necessary because of the large rule-base needed. Some of these libraries consist of words without structure and context, and some do not have syntactic annotations provided. More work will be needed to convert corpora into structures like parts-of-speech, morphologically related words, and syntactic structures.

2.3 Sentiment

According to Jurafsky and Martin (2009), the goal of Natural Language Processing is to get computers to perform tasks involving human language so as to improve human-computer communication through useful text or speech processing. The main thing that differentiates language-processing systems from other kinds of data processing systems is the use of the knowledge of language. A system that can be accepted to process Natural Language must necessarily have knowledge about lexical semantics (the meaning of words) as well as compositional semantics, which deals with how to combine the meanings of individual expressions and the relations they bear to one another. It must also have knowledge of the relationship of the words in the text to the syntactic structure. It would also need to have pragmatic and dialogue knowledge so as to answer questions in discourse. To engage in complex language, therefore, various kinds of knowledge of language required include

- Phonetics and Phonology — knowledge about linguistic sounds
- Morphology — knowledge of the meaningful components of words
- Syntax — knowledge of the structural relationships between words
- Semantics — knowledge of meaning
- Pragmatics — knowledge of the relationship of meaning to the goals and intentions of the speaker.
- Discourse — knowledge about linguistic units larger than a single utterance

Throughout this research, one of the foundations I have tried to explain is the question that gives rise to the need for affect-detection or sentiment analysis: Does a piece of text express a positive or negative sentiment? This seemingly simple question has proven to be quite complicated to solve, and is still an open problem for researchers in the Natural Language Processing (NLP) field. Even though it is so complex, a good answer to this question has a number of useful applications including the discovery of a product's presence online, checking the user feedback using reviews on a product or service, and offering customer support based on feedback.

Sentiment analysis, which I would want to re-label as affect detection, has also been described by the term opinion mining (Liu, 2015; Liu et al., 2005), semantic orientation (Osgood et al., 1957) and contextual valence (Polanyi and Zaenen, 2006). Other researchers have reference it as Opinion extraction, sentiment mining and subjectivity analysis. It is a method that is used to tease out the emotion conveyed by any piece of text or document. It seeks to answer the question as to the type of attitude that the text conveys. Scherer (1984) has defined attitude as a *relatively enduring, affectively coloured beliefs, references and predispositions towards objects or persons* and these can be grouped under general categories like *hating, desiring, loving and liking.* In cases like those presented by Polanyi and Zaenen (2006), all the words in a given piece of text are grouped into higher-level, relative sentiments of positive, negative and neutral. As stated earlier, the term affect here is used loosely to cover terms including, but not limited to, sentiment, semantic orientation, textual polarity, opinion, affect itself, emotion, attitude and valence score. Some researchers have attempted evaluating the sentiment orientation of documents by assigning polarities to expressions (words and phrases that are deemed to express opinions, emotions and sentiments), and then computing, in some manner, the overall polarity of the full document. (Pang et al, 2002; Turney, 2002; Hatzivassiloglou and McKeown, 1997; Kim and Hovy,2004; Yu and Hatzivassiloglou, 2003). Others have gone on to assign different strengths of evaluated polarities, and shown the degree of positivity or negativity of words and phrases and even whole documents (e.g. Wilson et al., 2004). SentiWordNet (Esuli and Sebastiani, 2006) computes three values of each synset in WordNet (Felbaum, 1998) and these values represent the degree of positivity, negativity or neutrality of a word, with the total sum of these 3 scores being 1. There is also Opinion Finder (OF), which was constructed by Wilson et al. (2005) to identify the sentiment of the writer.

As mentioned earlier in the introduction, there has been much study in recent years which aim at automatically determining the sentiment, emotion or attitude of a speaker, to evaluate the overall polarity of a text or discourse, where polarity here refers to the degree of negativity or positivity of a piece of text. The ability to rate a document by teasing out its emotion is desirable in several applications, including in everyday mundane chores. Business providers are increasing the level of encouragement to their customers to give positive reviews for goods and services purchased, knowing that future consumers will base their affect towards these goods and services on the recommendations of other users.

Sentiment analysis has been used to examine the sentiment in areas like the stock market (Nguyen and Shirai, 2015) which helps investors to make more financially sound investments; in movie reviews (Scheible & Schütze, 2013) which helps by acting as a marketing tool as well as a predictor of how well a movie will do financially; and in the political domain to predict the outcome of elections (Chung & Mustafaraj, 2011).

The proliferation of the WWW has made it easy to advance the research in sentiment analysis or opinion mining, by providing large data sets from social networks like twitter. The approaches that have been used for sentiment classification have included the use machine learning to learn sentiment patterns in annotated data (Dave et al, 2003; Pang et al, 2002) and the study of lexical resources used for sentiment analysis in order to analyse semantic orientation (Hatzivassiloglou & McKeown 1997).

The complexity in affect detection comes about because of a number of things that make it specifically hard. These include the following:

1. Negation is one of the reasons why a bag of words model doesn't quite work as a good solution to sentiment analysis. Simple statements like "*I liked the services that were provided*" and its direct negation "*I did not like the services that were provided*" will likely be similarly scored by a classic bag of words machine learning approach.

2. Mixed sentiments in the same piece of text arise when we have a complex sentence. A complex sentence can be made of different sections that have different polarities. A typical example could look like "*The service at the hotel was absolutely fantastic, but I wish it was better situated*". In this example, there are two different sentiments present and the task of extracting the meaning to know whether or not the location of the hotel has put the writer off so badly that they will not patronize it again becomes complex. A simple polarity aggregation may end up with a neutral score, which will be an error because the sentiment in the statement is definitely not neutral.

3. The presence of figurative language like metaphors, sarcasm and irony, and general humour like jokes, are extremely complex phenomena that are still not adequately understood theoretically, and so programming them has been difficult. An example like "*Luke is one special human being!*" is most likely a case of sarcasm, and so *special* will not be playing its classic, positive meaning here. "*Paul is a rat!*" also is metaphoric, and does not seek to say that there is a rat named Paul.

Because of the complexity of finding solutions to these problems, it is reasonable to tailor algorithms to suit the domain for which an affect detection system is being created. For example, if it is to work in the food industry, there must be a great consideration for all kinds of food language, including metaphors and other literary devices. If the system is for social media like twitter, emoticons will play a big role. If it is to be used on the political front to, for example, predict election results, current events of the political scene must be taken into consideration.

2.3.1 Categories of Sentiment

A lot of work has been done in sentiment classification by using the binary sentiment category approach (Pang et al., 2002) but this has implied that every document must necessarily have an associated polarity. This is not the case in practice as a number of words have proven to be neutral (Polanyi & Zaenen, 2004). It has been found that working with the neutral classification can be quite problematic since it becomes difficult to differentiate between a neutral sentence and a weak-sentiment document (Kim and Hovy, 2004).

Polanyi and Zaenen (2006) attempted to have a better way of annotating the adverbs in a document by assigning integer polarity values from +2 for strong positive to -2 for strong negative with 0 as neutral. Their conclusion however was that this system, though finer-grained, is still too coarse to use to concretely determine the level of polarity even though they considered inter-annotator agreement to reduce the level of subjectivity. Taboada et al (2011) also annotated adjectives, adverbs, nouns and verbs of a specified corpus in an attempt to achieve an even finer-grained scale of evaluation. Though it has a level of subjectivity, the use of both inter-annotator agreement and dictionary comparison studies allows their scale to be quite robust.

There arises the problem of having a concrete mapping between the sentiment intended by the writer (or speaker and more generally, the initiator of the discourse), and the sentiment understood by the recipient (and/or listener). There was a proposal to classify documents as being either objective or subjective (Volkova et al., 2013; Abdul-Mageed et al., 2011; Rilof and Wiebe, 2003) but some (Scheible & Schütze 2013) have argued that this is not an optimal method as some objective statements, though not directly exhibiting the state of the writer, have a bearing, whether direct or indirect, on the overall document's sentiment. It is note-worthy that different research projects analyse sentiment at different grains, from single lexical units through sentences to whole documents, and the different grains have different practical uses.

2.3.2 Rule-based Approaches to Detecting Affect

Rule-based affect-detection or sentiment analysis approaches are based on manually crafted rules and lexicons, and several works have been done in this area.

Boiy et al (2007) described how rule-based approaches make use of lexicon-based techniques using web searches and WordNet. In their research, they discussed how web searches provide useful data like the frequency of words used in a piece of text, the various term distributions, and how words co-occur. WordNet, however, shows the links and relationships between words, and can show how far away one word is from another, by counting the distance between them using nodes.

Turney (2002) used a web search approach to also determine the affective orientation of adjectives, using the Altavista Search engine and its NEAR function. He did this by calculating the co-occurrences of adjective-nouns and verb-adverbs, and concluded that those near "excellent" are positive while those near "poor" are negative.

Kamps et al (2004) also created a system using WordNet and Osgood's (1966) dimensions of meaning attribution (evaluation, activity and potency) to evaluate the sentiment of words. Their system essentially used the shortest path between nodes to determine their polarity. The problems identified in this work were that not all words are represented in the corpora, and not all words were connected to either a negative or a positive prototype.

In all the above-mentioned works, the context of words was not considered. Also, sub-sentential interactions were not captured, even though their impact is very important in assessing large sections of text.

There is the Principle of Compositionality, which states that the meaning of a complex expression is a function of the meaning of its parts and of the syntactic rules by which they are combined (Montague, 1974; Dowty et al., 1981). Moilanen and Pulman (2007) therefore created the idea of sentiment compositionality where polarity values were assigned to individual words within a given text, and then an overall value was determined. They used an affective lexicon which contained a list of manually compiled words and had specific polarities assigned to them, and was further expanded using WordNet 2.1. Polanyi and Zaenen (2004) added the effect of contextual valence shifters. These valence shifters, according to them, include simple negatives (e.g. not, never, none, nobody, nothing, neither), intensifiers (e.g., rather, deeply), modals (e.g., if, were, would), presupposition items (e.g., barely, even), and contextual valence shifters (e.g., although, however, but, on the contrary, notwithstanding). After experiments, they concluded that using valence values to determine the affect (or attitude) of a discourse is simply too crude and needs more refining. Another approach was described by Klenner et al (2009) where they used a pattern-based approached called PolArt, in which a cascade of re-write operations were carried out (word polarities were combined to NP, VP and sentence polarities), which allowed them to capture the effect of valence shifters in order to ascertain the polarity of larger volumes of text. PolArt made use of the Subjectivity Lexicon (Wilson et al., 2005) to try to obtain the valence of words. These approaches, though able to handle the structural nature of interactions between sentences, could not properly manage language ambiguities, mainly due to the fact that context was not taken into consideration.

2.3.3 Machine Learning Approaches in Sentiment Analysis

Machine learning (ML) is a branch of Artificial Intelligence, and uses algorithms to allow computers to "learn" (Segaran, 2007). This means computers will be able to act without being explicitly programmed to take an action. It works by allowing information to be fed into a computer, and the computer using this knowledge to infer information about characteristics of the data, which is subsequently used to make predictions about other data sets. This inference is made possible because of patterns that are contained in non-random data. The computer can save information about what it determines to be important aspects of data, and uses that knowledge in "thinking" and inferring information about other data. This learning process can be classified under supervised, unsupervised or semi-supervised learning.

Supervised Learning is a computational methodology of learning the correlations that exist between a set of variables in some annotated data (referred to as the training set), and using the information obtained to produce a predictive model that is able to infer new annotations for a new data set whose annotations are not previously known. In this sense, a predictive function f maps the predictor attributes x of an instance, to a prediction y which is the target variable (or the non-annotated variable) of the instance, given a set of training data (or instances) that are represented by tuples in the form (X_i, Y_i) with Y_i being the target variable and X_i being the vector which typically contains a numerical and/or categorical value, and which has an encoded predictor feature associated with the ith instance (Witten et al., 2011). This process is referred to as a *classification* if the target variable Y is categorical i.e., being nominal or discrete, and *regression* if Y is continuous or real-valued. Some popular supervised ML algorithms include Linear Regression (for regression problems), Random Forest (for classification and regression problems), and Support Vector Machines (for classification problems).

Unsupervised learning refers to a system that has the ability to learn and organize data without having previously assigned annotations from which to compare with in order to propose a potential solution. The aim for unsupervised learning is to model the underlying distribution of data in order to learn more about the data. Its lack of training data in the form of corresponding output values can be advantageous as it allows the algorithm to revisit previous datasets to look for patterns that have not been previously identified (Kohonen and Simula, 1996). Unsupervised learning techniques can be grouped into *clustering problems* which have an aim to discover inherent groupings in data, and *association rule learning problems* which aim at discovering rules that describe large portions of a given data such as people in the hospitality industry tending to use metaphors that relate to food. Popular unsupervised learning algorithms include K-means (for clustering problems), and Apriori (for association rule learning problems).

In semi-supervised learning problems, the input data is a mix of labelled and unlabelled (a greater portion) data, and the learning model is expected to learn the structures well enough to organise the data as well as make correct predictions. A good example would be having a large list of words with only some being labelled as positive affect-bearing words, and a good number of real-world machine learning problems fall into this category. This is because it could be quite expensive and/or time-consuming to label all data in the domain being worked in, typical example being the ability to get experts to label all data in some specified conceptual metaphor domain. Unsupervised learning techniques can be used to learn and discover structures within the input variables, and supervised learning techniques can be used to make best guesses from the unlabelled data that will be fed back into the system in order to make predictions on new and unseen data.

Tackling the problem of labelling data for sentiment analysis can be achieved by using the affect-bearing words approach, the word sense approach, or the bag of words approach.

2.3.3.1 Using Affect-Bearing Words

There are some words that are of a negative or positive polarity even without a context. Words like "bad", "terrible", "awful", "insensitive", "crude", "angry", "hostile", denote negative sentiment if evaluated independently. Words like "love", "happy", "good", "blessed", "fortunate", "joyous" and "kind" are also evaluated as having a positive affect. The use of these words within a document could be indicative of a writer describing the sentiment in a scenario, or the writer himself expressing his sentiment about a scenario, a distinction that appears to be absent in SA research. An example of this is given at a later section in this chapter. Since manually labelling corpora for supervised learning can be quite tedious and time-consuming, it is sometimes easier to use semi-supervised learning methods to construct labelled corpora for use in supervised learning.

Riloff and Wiebe (2003) typified this example by constructing an affect-word list using semi-supervised learning by starting with a few words that were sorted into positive and negative polarities, and then repeatedly expanded by updating with antonyms and synonyms obtained from WordNet (Miller, et al., 2004). This approach assigns polarity at either word or phrase level.

Hatzivassiloglou and McKeown (1997) used another ML approach that involved learning words with prior polarity knowledge. They manually segmented documents into clusters and labelled them positive or negative, using text from the General Inquirer (Stone, 1962) to achieve this. Opine (Popescu, Nguyen and Etzioni, 2005) explored using the semantic relationships between words, to aid in determining the orientation of sentiment. This was on the premise that a word can change polarity based on the context within which it is used (e.g., *hot water* is not necessarily negative and could be positive, but *hot temper* is most certainly negative). Esuli and Sebastiani (2006) used Semi-supervised learning to determine the orientation of words by examining glossary information on their glosses as provided in WordNet. This was on the premise that words with similar orientations will have similar glosses.

Some machine learning methods have also sought to compute sentence-level affect, by assigning word polarities and averaging those polarities, as done by Yu and Hatzivassiloglou (2003). Polanyi and Zaenen (2004) however showed why such methods might be too crude to give accurate results.

2.3.3.2 Using Word Sense

The sense-tagged lexical resource, SentiWordNet, was developed to assign word-senses with polarity that is aimed at enhancing Word Sense Disambiguation (WSD). In the development of SentiWordNet, the relations of synonymy and hyponymy were considered. There is a bit of scepticism on the assumption that synonyms of negative and positive words are also negative and positive respectively. There is, however, no absolute synonymy among words, and depending on the context within which it is used, a synonym of a positive word could turn out to have a negative connotation. For this reason, Matín-

Wanton et al (2009, 2010) focused on modifying the WSD step, and addressed the issues in sense-level tagging.

For example

She walked into the room

She trudged into the room

Trudged is a synonym of *walked* (which could be neutral or positive in polarity) but in the second sentence, it denotes a negative polarity. In this case, the negativity of *trudging* describes the manner in which she walked into the room, and so though negative, it could be either 1) devoid of the writer's sentiment, and becomes an example of the case where a writer is *reporting* a sentiment; or 2) be subjective if the writer is unhappy about the manner in which she walked into the room, becoming a case of the writer *expressing* a sentiment. In their approach, Matín-Wanton et al (2009, 2010) used the Extended Star Clustering Algorithm (Gil-García et al., 2003) to cluster all possible WordNet senses of ambiguous words that occur, and select the senses that best fit the target words. If it is noted that the clusters have disambiguated all the words in a sentence, the process is halted, otherwise it continues. The total sentiment is computed by averaging the polarity scores of all the word senses.

From analysing these approaches, it can be concluded that it is preferred to disambiguate words before assigning polarities to them, to enable overall polarity to be determined for sentences.

2.3.3.3 Using Bag of Words

This method is a way of representing text that involves describing the occurrence of known words in a document. The term "bag" is used because this representation does not take into consideration the structure of the words, the order in which they occur, or the places in which the occur.

When a set of documents is obtained, a list of all the unique words are made. Document vectors are created, and these vectors are used to represent each document. To avoid the occurrence of sparse vectors and subsequently, sparse representations, which require more memory to process, simple text cleaning techniques like ignoring cases (upper or lower cases), ignoring punctuation commas, full stops, etc.), ignoring stop words (words that don't contain much information like "a", "of"), fixing misspelled words, and reducing words to their stems (e.g., "run" from "running) can be employed. More sophisticated approaches like bigrams (two-word pairs, e.g., "I am", "am very", "very hungry") and trigrams (three-word phrases, e.g., "I am very", "am very hungry") could also be used to reduce the size of the vocabulary. Once the vocabulary is done, there is a binary scoring of the words.

Though the bag of words is very simple to understand, implement and offers a lot of flexibility for customization, it requires that the vocabulary be carefully designed in order to manage the size, which impacts the sparse representation, impacting on space and time complexity. In general, research from some Bag-of-Words models have shown a limitation of flat sentence representations, and are unable to capture the semantic and word interactions that exist within a sentence. They therefore become insufficient in determining the overall polarity of shorter extracts of text where the ordering of words can affect the overall sentiment deduced.

For example,

(a) Honestly, they couldn't have won the contest.

(b) They couldn't have won the contest honestly.

The sentences (a) and (b) contain essentially the same words, but convey sentiment of different polarities. In (a), the sentiment is positive as the speaker (or writer), by placing the adverb *honestly* in the beginning of the sentence, expresses an agreement with their excuse for not winning the contest. In (b) however, it presupposes that they won the contest, but through dishonest means. The bag-of-words classifier will be unable to tell the difference in the polarities since both statements will have the same bag-of-words representation.

2.4 Metaphors and Affective Communication

Conveying affect is one important role for metaphor, and metaphor is one important way for conveying affect (Rumbell et al, 2008). In this section, I examine the relationship between metaphor and affect,

2.4.1 The Relationship Between Metaphor and Affect

It can be suggested that metaphors are a way of communicating in such a way so as to send a message across with an unmistakable picture attached. This is to say that metaphors are key when trying to send across an emotion as they paint a picture in a hearer's or reader's mind. For example, a teacher tells his student that "regularity and punctuality conquer the mountains". According to the metaphors dictionary (Sommer, 2001), metaphors that include *mountain* are quite common, and examples are given of *to make a mountain out of a molehill* and *a mountain of work* or *problem*. Taking into consideration the layout of a mountain and just how tedious or impossible it may be to climb one, we immediately picture a difficult situation or a problem that needs to be overcome. Again, a main aim for metaphor usage is to convey affect so that instead of saying *I love absolutely everything about her and I cannot get enough of her* (or some similar intent), one can simply say *I am crazy about her*, which comes under the conceptual metaphor of *LOVE IS MADNESS*. As another example, instead of saying *He is going around the whole place, showing people how much money he has by spending a lot and appearing rich*, one can simply say *He is flaunting his wealth*, which falls under the conceptual metaphor of *WEALTH IS A HIDDEN OBJECT*. A list of examples of expressions from the conceptual metaphors of two emotion concepts, anger and love, are listed below from Kövecses (2000):

ANGER:

ANGER IS HOT FLUID IN A CONTAINER: She is *boiling with* anger.

ANGER IS FIRE: He's doing a slow burn. His anger is *smouldering*.

ANGER IS INSANITY: The man was *insane with* rage.

ANGER IS AN OPPONENT IN A STRUGGLE: I was *struggling with* my anger.

ANGER IS A CAPTIVE ANIMAL: He *unleashed* his anger.

ANGER IS A BURDEN: He *carries* his anger *around* with him.

THE CAUSE OF ANGER IS TRESPASSING: Here I *draw the line.*

THE CAUSE OF ANGER IS PHYSICAL ANNOYANCE: He's a *pain in the neck.*

ANGER IS A NATURAL FORCE: It was a *stormy* meeting.

ANGER IS A SOCIAL SUPERIOR: His actions were completely *governed* by anger.

LOVE:

LOVE IS A NUTRIENT: I am *starved for* love.

LOVE IS A JOURNEY: It's been a *long, bumpy road.*

LOVE IS A UNITY OF PARTS: We're *as one*. They're *breaking up*. We're *inseparable.*

LOVE IS A BOND: There is a close *tie* between them.

LOVE IS A FLUID IN A CONTAINER: She was *overflowing with* love.

LOVE IS FIRE: I am *burning* with love.

LOVE IS AN ECONOMIC EXCHANGE: I'm *putting more into* this than you are.

LOVE IS A NATURAL FORCE: She *swept* me *off my feet*.

LOVE IS A PHYSICAL FORCE: I was *magnetically drawn* to her

LOVE IS AN OPPONENT: She tried to *fight* her feelings of love.

LOVE IS A CAPTIVE ANIMAL: She *let go of* her feelings.

LOVE IS WAR: She *conquered* him.

LOVEI S INSANITY: I am *crazy about* you.

LOVE IS A SOCIAL SUPERIOR: She is completely *ruled by* love.

LOVE IS RAPTURE / A HIGH: I have been *high on* love for weeks.

THE OBJECT OF LOVE IS A SMALL CHILD: Well, *baby*, what are we gonna do?

THE OBJECT OF LOVE IS A DEITY: Don't *put* her *on a pedestal*. He *worships* her.

The words used in metaphors show various aspects of emotion concepts which are instances of conceptual metaphors in the sense as described by Lakoff and Johnson (1980), which involves creating a correspondence between a typically more physical or concrete domain, and a largely abstract domain, with the aim that the more abstract will be understood in the context of the more concrete. Figure 1 gives a summary of types of emotion language

Often, emotional states and associated behaviours are themselves described metaphorically (Kövecses, 2000; Fussell and Moss, 1998). Kövecses talks about the figurative emotions in the English Language and itemizes the conceptual metaphors of emotions including happiness, lust, pride, shame and anger, and suggests that people largely use metaphorical language to talk about various kinds of emotions. He also carried out an examination of the link between Lakoff's (1990) event structure metaphor, and emotion metaphors, and concludes that there is a master metaphor for emotions, an example being EMOTIONS ARE FORCES. In his diagrammatic summary (figure 1) of the types of emotion language, however, Kövecses does not give any subdivisions of the expressive forms of emotion language.

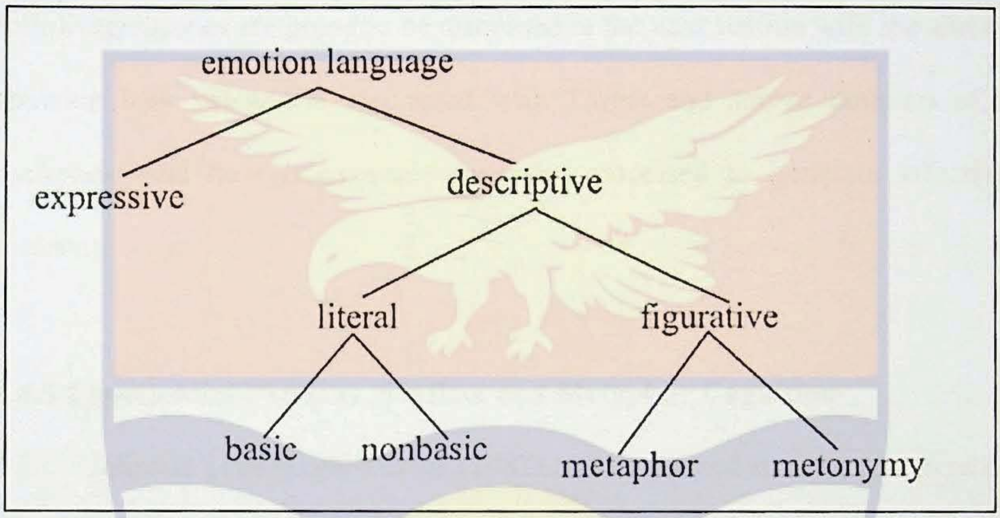

Figure 1: A summary of the types of Emotion Language
Reference: Kövecses, 2000

2.4.2 Overview of Affect and Metaphor Comprehension

In order to understand what affect contributes to metaphorical meaning, I consider four theories of metaphor comprehension that have a lot of support from research in psychology: the conceptual structure, the salience imbalance, class inclusion and structure mapping. Each of these theories projects a unique mechanism for comprehending metaphors but they all submit that interpretation of the metaphor of type *A is B* uses knowledge that is relevant to both A and B, which I will term as *target* and *source* respectively. It would be expected that the knowledge about both A and B would include affective as well as cognitive information, but in some cases, the various processing mechanisms concentrate largely on how the cognitive knowledge about the target and the source is used to construct the cognitive meaning of any given metaphorical expression with little mention being made of explicit affect and affective meaning. The following theories are going to be discussed in the next section with the aim of showing how valence is associated with Target and source domains of a metaphor, and how interpretation can be processed to generate affective meaning.

2.4.3 Experiential Patterns of Affect and Metaphor Cognition

Johnson (1987) and Lakoff (1987) both proposed that the structure of simple domains that are mapped unto more complex domains, are the result of bodily interactions with the world. Damasio (1994) however shows that the human brain has a way of attaching a valence value to every incoming stimulus during early stages of stimuli processing. It therefore stands to reason that the structures suggested by Lakoff and Johnson should be represented to indicate each perception-valence pair since both are embodied in a stimulus and are therefore related. To expatiate further, let us consider the conceptual metaphor *LOVE IS A JOURNEY*. According to Lakoff (1992), the mappings for *LOVE-AS-JOURNEY* will include

- *The lovers correspond to travellers.*
- *The love relationship corresponds to the vehicle.*
- *The lovers' common goals correspond to their common destination on the journey.*

- *Difficulties in the relationship correspond to impediments to travel.*

From the mappings, and comparing with ordinary journeys, I conclude that the ability to reach one's destination and any other happy encounters during the journey will be of a positive emotion, while disruptions, difficulties or even a discontinuation of the journey will be of a negative emotion. There will therefore be affective information alongside the cognitive mappings. Because the metaphor is understood through the ·mapping process between the knowledge base of target and source, the affect enters the cognitive comprehension directly through the inherent valences associated with the base and target by the mappings.

Let us consider an expression like *This relationship isn't going anywhere* (Lakoff and Johnson, 1980). In using the cognitive sense that *the relationship is a journey* and that *a journey should end at a desired destination,* a journey that goes nowhere denotes a fruitless endeavour that is a waste of time, energy and resources, and therefore shows an expression that consists of both a cognitive and affective meaning, in this case, a negative affective meaning.

There could be instances where the conceptual metaphor is largely neutral in its affect, and so results in metaphoric mappings that are neither intensely negative nor positive in their valence. A good example will be *LOVE IS AN IMAGINED THING*, which results in mappings that include "imagery", 'phonological passes", "analogies" or "Things not physical". Relating metaphors will include *A vision of Love. I didn't realise the dream, The love that came to be.*

In any of these cases, the imagination of the person in question is purely based on the person's psychological state (positive negative, neutral) at the point of stating the metaphor. Another example of a concept that could be neutral is *MIND IS A CONTAINER,* which results in mappings that include enclosed spaces that deals with things like "enter", "exit" and "remain in". Relating metaphors will include *The thought came into my* head and *He took the idea and turned it over in his head*. In extending that metaphor to something like *Minds are like parachutes – both work only when open*, then we can begin to understand intuitively the essence of a parachute and the implications of a closed parachute at a certain critical moment. In this case, knowing that a functional parachute is good becomes a good place to start evaluating the affective element in the metaphor. It is also a matter of interest to note that if the parachute opens up within a plane that is on its way to a crash landing, which will result in a bad consequence, it helps to know the kind of valence to attach, though we have already implied that an open parachute is good. Relating it to the mapping, being open-minded about hard drugs enough to try it and get addicted, will not be a positive emotion, same as an open parachute in a plane. Context is therefore important. In extracting affective meaning of metaphors therefore, the affective information that is related to the target and source relates with the affect that is incorporated in the relevant conceptual metaphor. The final valence of that metaphor will therefore be an aggregate of the associated valence of the conceptual metaphor, the target and the source.

2.4.4 Affect as an Attribute and Metaphor Cognition

Bower (1991), Fiske and Pavelchat (1986), Ortony et al. (1988) and Thagard (2001) have sought to project affect as a purely cognitive model of psychological function and termed them as valence "tags" that are attached to cognitive elements. In this case, there appears to be two interdependent ways in which affect acts as an attribute – as an attribute of a cognitive property of an object or category, and as an attribute of an object itself. In their view, every piece of cognitive information has a positive or negative valence tag associated with it, and these tags are of varying intensities. The elements are perceived at different levels. For example, a category of objects could be utensils of which a frying pan becomes an object in that category, and the lid of the frying pan becomes an attribute of an individual object. Fiske and Pavelchat (1986) conclude that an affective tag can be attached to an element at any of these levels. Affect integration during metaphor comprehension may be achieved through salience imbalance, class inclusion or structure mapping theories of metaphor comprehension.

2.4.4.1 Salience Imbalance Theory

For any two elements under comparative study, the shared attributes will have an imbalance in terms of rank of importance, and this forms the basis of the Salient Imbalance Theory. As an example, for the metaphor *His words are a two-edged sword*, the object of comparison (topic term) is *words* while the term being used to describe the topic (vehicle term) is *two-edged sword*. In this particular example, a listing of possible characteristics of the topic term *words* will include *for comforting, for inflicting pain, for rebuke, for communication, may be sharp and painful, may be soft and soothing,* etc, and possible characteristics of *two-edged sword* will include *very sharp, ability to cut, ability* *to inflict pain, ability to sever off,* etc. When these attributes are compared, one that could be a shared attribute will be *sharp,* which is of a low salience to *words* but of a high salience to *two-edged sword,* thereby creating an imbalance. Ortony (1979; 1993b; Ortony et al., 1985) proposed the Salient Imbalance Theory as a way of understanding metaphors. He defined *Salience* empirically as the relative importance of an attribute, this relativity being based primarily on the attribute that first comes to mind when a word or phrase is used, with the assumption that the first that comes to mind is the most salient. According to his theory, a constructive ground is used in metaphors of type "A is B" to denote shared attributes of A and B, and this set of shared attributes will be inclusive of only the ones that have low salience for the target ***A*** and a high salience for the source ***B***.

2.4.4.2 Class Inclusion Theory

Glucksberg and Keysar (1990, 1993) proposed the class inclusion theory that suggests that all metaphorical expressions of the form ***A is B*** are what they look like, and so they become statements of assertion of a categorization rather than statement of implicit comparison. Such metaphors activate recognizers to construct an immediate superordinate category for the source, treating the source as a prototype of the category, and then making the target the latest addition to that category. So, for the statement *Her home was a prison*, a superordinate category that is likened to "restrictive things" is constructed which has a typical member *prison*. *Home* is then added into this category and so inherits all attributes (e.g., restrictions, freedom loss, isolation) associated with the category, which helps in understanding the metaphor for what it is. In this case, the affect can be derived based on the valence orientation of the category of restrictive things.

2.4.4.3 Structure Mapping Theory

According to Gentner (1983), the theory of analogy must describe the process of extracting the meaning of an analogy from the individual meanings of its composing parts. In this sense, the rules that are used to interpret meanings are characterized as implicit rules that map the knowledge of a base domain unto a target domain. Two important aspects of this theory are that the interpretation rules are dependent on only the syntactic properties of the knowledge representation and not specific content of that domain, and that the theoretical framework allows analogies to be clearly distinguished from literal similarity statements as well as abstractions and other types of comparisons. As an example, if I were to say *Tom is like a lion* a literal similarity comparison will be teasing out the features that are common to both *Tom* and *a lion*, which could include both having red blood, both having hair (even if Tom is bald), bother being living creatures that breathe, and both being able to move. This literal comparison works only to a certain point and does not give a strong basis for deep analogy, and so though feature overlap works, it doesn't take analogy very far. It is also the case that not all features are relevant for the analogy I may intend to make. For proper analogy, the essence of the mapping between *Tom* and *lion* would be to point out that both are territorial (lions are known to be highly territorial and can occupy the same area for a long time with the lionesses actively defending their territories while the lions protect their prides from rivals, all these possibly describing Tom's character), intimidating (adult males are much larger than females, and could be describing Tom's physical appearance), and symbols of authority (being known as the head of the pride, and so Tom could be the head of a group of people). The central idea of structure mapping therefore, is that a relational structure which is normally applicable in one domain, can be correctly applied in another domain. Concerning metaphor and structure mapping, Gentner (1982, 1983, 1989; Gentner and Clement, 1988) proposed a structure mapping theory that allows a comparison of lists of attributes, checking for similarities to allow metaphor interpretation. Gentner says that metaphors are explicitly linked to analogy, and becomes an acceptable assertion that a relational structure that is normally used in one domain can be applied in another domain in a way that shows the intent of the speaker. It therefore makes metaphors as pieces of text that connect several knowledge domains. People attempt to interpret metaphors by obtaining a structural match between target and source using relational mappings. In the example, *Her home was a prison*, a mapping will be defined from *prison* to *home*. *Home* will be labelled as the target since it is that domain that is being explicated, while *prison* will be labelled as the base, since that is the domain that will be serving as the source of knowledge. The statement will therefore be interpreted by finding the common restriction relation of the home and its occupant, and then the restriction relation between a prison and its occupant. In this way, affect can be obtained from the common relational mapping. A good grasp of this mapping system therefore allows a cognitive attribute to be evaluated without being explicitly stated.

Affect in metaphors can be illustrated as an attribute of an attribute. In a simple *A is B* metaphoric expression such as Love is War, the target, Love, and the source, War, will contain several attributes of cognition that will have either a positive or negative valence of variable intensities. These tags can be seen as attributes of the attribute themselves. For example, attributes about the target *Love* include, but is not limited to, happiness, euphoria and peace. Attributes about the source *war* will include strife, death, unhappiness, fear and starvation. These listed attributes can each be valued with either a positive or negative valence.

2.4.4.4 How the Approaches Aggregate Affect

The salience imbalance view will get its primary valence from the salient attributes of the base and the non-salient attributes of the target, which will be put together to form the neutral ground on which the meaning will be built (Hitchon et al., 1996). If the salient attributes of the source give a positive valence and the non-salient attributes of the target also give a positive valence, then these will form the ground on which we can conclude that the metaphor is positive.

The class inclusion view will find the valence associated with attributes that have been inherited from an on-the-spot superordinate class, and this will greatly influence the process by which the metaphor is understood. Thus, the target will have a superordinate category from which the source inherits. As a consequence, the overall valence will be derived from the valence of the constituent valences.

Using the structure mapping view, the final valence will be based on the relational mapping that exists between the attributes of the source and those of the target that are commonly positioned in the relational structure.

In all these three mechanisms for extracting affect, the valences of the individual attributes play a key role in categorizing the affective value of the sentences.

2.5 Modifiers

The work in this thesis has a heavy reliance on modifiers and so in this section, I present an overview of what they are and how they are used in everyday English language. For the purposes of this study, the word *Modifier* is being used in a very broad sense to include all words that limit, enhance, qualify or modify a word in any way, and our focus is on those modifiers that are placed immediately before the words they modify. A number of research works that have been done on evaluating the strength of opinions within a sentence or document have used specific parts of speech such as adjectives, verbs and nouns, and any of these words, if they modify another word just after them within the sentence in which they occur, become of interest to us in our study. Broadly speaking, adjectives qualify nouns and adverbs modify verbs, but for grammatical purposes, both of them do the same work - they limit the meaning of other words or parts of speech. In treating modifiers, adjectives and adverbs are taken as one, and other ways of modification are considered. For the purposes of this paper, I will use the word ***modifier*** to include and refer to both modifiers and qualifiers.

There are several positions that modifiers can be placed within sentences, and the placement is usually determined by the intent of the initiator of the discourse as they decide on which words or phrases they may want to emphasise or clarify. There are modifiers that are placed immediately before the words they qualify, as opposed to being placed anywhere else within a sentence. An example would be *Peter is wearing a red shirt*, where the *red* qualifies the shirt that Peter is wearing. A variation of this statement would be *Peter is wearing a shirt that is red.* I could even break it down into two separate sentences: *Peter is wearing a shirt. The shirt is red.* Both the single and pair statements achieve the same purpose of describing the colour of the shirt that Peter is wearing. Even with such simple examples, there could be several adjectives put together to give more detail and create a fuller picture. I could therefore decide to add more modifiers to achieve a statement like

> *Peter, the red-haired gentleman who walks his dog in the park every Saturday morning, is wearing a dark red shirt with an obvious stain on the left side, just above his breast pocket.*

The structure of a modification contains a *head* and a *modifier*. A *modifier* therefore is a word as in: Bushy hair and grey beard – to characterize appearance. The modifiers *bushy* and *grey* are modifying the nouns *hair* and *beard*, which are nominal heads in their respective sentences. There are other kind of modifiers with nominal heads as in

> *Iron can rust*

Cotton grows well in Egypt.

The head words (underlined) which are nouns, can be made modifiers in the following variations of the sentences where they serve as modifiers:

An iron bar

A cotton shirt

When nouns are placed before other nouns, they modify the succeeding nouns:

A bus stop to explain that it is a stop for buses;

Shoe lace to specify a lace for shoes;

Watch strap to explain that it is a strap for watches.

The underlined words are all modifiers, though nouns. Modifiers can therefore occupy different positions in sentences as in

The man is very tall

His speech is much better

The hunter bought a new gun

Adjectives also perform modification functions on the words that they precede. Typically, *interesting* is an adjective which when used in a sentence like

The teacher read an interesting story

modifies the meaning of the *story* that was read.

Though there are several types of modifiers including squint modifiers (For example *Students who watch a lot of movies occasionally sleep off in class*) and dangling modifiers (*Without any weapon, the thief escaped*), I will limit our usage of modifiers to words placed before other words to qualify their meaning in some way. Examples would include sentences like

He purchased a Persian rug for his living room.

where *Persian* qualifies *rug* and *living* qualifies *room*.

Because modifiers can help describe the meanings of sentences, they can consist of all types of parts of speech including adverbs and adverbial clauses, adjectives and adjectival clauses, prepositional phrases, infinitive phrases, absolute phrases and particle phrases. When used skilfully, modifiers can make a piece of text become more detailed, interesting and engaging for a reader. They can also be used to give more information, thereby creating a fuller picture for a reader. To show the power of modifiers, let us consider the following simple sentence;

Ernest is a brilliant child.

This sentence can be replaced with multiple modifiers as:

The tall blue-eyed toddler named Ernest, who is the son of Mr. and Mrs. Banning, the Ghanaian couple who live down the street next to the bakery, has exhibited remarkable cognitive, emotional and social development since he was enrolled in the nursery, and has proven to be a totally brilliant child.

The use of modifiers in the correct manner adds extra details to a sentence without necessarily being superfluous, and can be a brilliant way of engaging readers and holding their attention.

Let us consider another example

Adwoa gathered ingredients

Using the types of modifiers outlined earlier to qualify this sentence, will give a much fuller picture and create a complex story from this simple sentence by adding extra details. The sentence can therefore be re-written as

Youthful and energetic ***Adwoa****, who just wanted to eat her favourite flavour of cake to reward herself, enthusiastically* ***gathered*** *the* ***ingredients*** *from the kitchen store, popping bits of sugar and chocolate into her mouth and leaving a trail of flour on the floor as well as the kitchen table, a situation that required Auntie Ama to spend so much time to clean up such that she couldn't get time to help Adwoa bake the cake.*

This enhanced sentence, though long, tells much more of the story than the first sentence, and is also more interesting to read and would likely pique a reader's curiosity to want to know the end of the story by asking questions like

- *What did Adwoa want to reward herself for?*
- *Why couldn't Auntie Ama help her with gathering the ingredients in the first instance?*
- *How did a trail of flour become so much work that it took an entire baking time to clean up?*
- *What type of cake was Adwoa going to bake?*

The enhanced sentence also contains at least one of each of the following types of modifiers:

- Adjective (*describes a noun or a pronoun*): youthful, energetic
- Adjectival clause (*a descriptive phrase that acts as an adjective*): *who just wanted to eat her favourite flavour of cake*
- Infinitive phrase (*a descriptive phrase that starts with an infinitive, or to, followed by a verb*): to reward herself

- Adverb (*describes an adjective or verb*): enthusiastically
- Prepositional phrase (*a descriptive phrase that starts with a preposition, or any other word like on, in or on top of*): from the kitchen store
- Particle phrase (*descriptive phrase starting with a verb in an adjective form, usually ending in –ing or –ed*): popping bits of sugar and chocolate into her mouth
- Adverbial clause (*a descriptive phrase acting as an adverb*): leaving a trail of flour on the floor as well as the kitchen table
- Absolute phrase (*a descriptive phrase that attaches to a sentence with no conjunction, often modifying the meaning of the whole sentence*): a situation that required Auntie Ama to spend so much time to clean up such that she couldn't get time to help Adwoa bake the cake.

2.5.1 Adverbs

An adverb modifies a verb, and by so doing, helps us to tell *how*, *when*, or *where* a particular action takes place. In a situation like *He walked…*, adverbs can be added to indicate the how, when and where as follows:

He walked slowly. (how)

He walked yesterday. (when)

He walked along the beach yesterday. (where)

They can also modify other adverbs, as in the case of

He walked very briskly to his car.

Adverbs commonly end in *–ly* with examples including *fatherly, lonely* and *lovely*. There are however many words and phrases without this ending but which also serve adverbial purposes, an example being *very*. Adverb clauses are a group of words that usually contain a subject and a verb, and act as an adverb by modifying the verb of the sentence. An example will be

When this project is over, I will have a party for myself.

There could also be a group of word that do not contain a subject and verb, but act as an adverb, and this would be called an adverbial phrase. Prepositional phrases also frequently have adverbial function and would often be used to tell the place and time to modify the verb. Examples will include

She went to the shopping centre.

Fred works on weekends.

They lived in Vietnam during the second world war.

Infinitive phrases also act as adverbs and usually tell whey an action happens. Examples would include

Adiza run to catch the last train.

There are also other kinds of adverbial phrases:

I travel to see my parents as often as possible.

Grammatically, adverbs can modify adjectives, but adjectives are not supposed to be used to modify adverbs. So, I could say *Her superior showed a really caring attitude* and then again, *The judge showed a wonderfully gracious composure*, but not *She ate real fast*. Even though the latter is not accepted in proper English grammar, it has become common language on the internet and in everyday usage. Adverbs can also have comparative and superlative forms to show degree, and examples would include

Eat faster if you want to go shopping with me.

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Eat faster if you want to go shopping with me.

The child that runs fastest will get the prize.

There are also times that *more* and *most*, and *less and least*, are used to show adverbial degrees, as in the case of

In flat shoes, she could move more easily among the tables.

The suit was the most neatly cut creation I have ever seen.

He spoke less confidently after being embarrassed the last time.

This is the least tasteful meal I have had in years!

A few adverbs also appear in two forms, one that end in *–ly* and one that does not, and in some cases, these two forms present different meanings.

Amina arrived late.

Lately, Amina cannot seem to be on time for any function.

Often, adverbs are also used as intensifiers, and they convey a greater or lesser emphasis. Intensifiers have three main functions – emphasize, amplify or downtone.

For emphasizers:

She literally dragged him by the hand.

He simply ignored his attraction to her.

I don't really believe the story.

For amplifiers:

I absolutely refused to be side-lined in the discussions.

They heartily ate to their fill.

He knows his way around the city well.

As downtoners:

She sort of felt betrayed by her husband.

The proposal can be improved to some extent.

He almost quit his job after the altercation with his superiors.

The positioning of adverbs in a sentence can be so flexibly done that it makes their use easy and interesting. An example would be

Solemnly, the speaker addressed the house.

The speaker solemnly addressed the house.

The speaker addressed the house solemnly.

The results here will be slight differences in the meanings communicated by the shifting positions of the word *solemnly.*

Let us consider another example:

I met him on the train last night

and, for illustration purposes, try to fix the modifier in several different places within the sentence.

- *Only I met him on the train last night* (No one else met him except I)
- *I only met him on the train last night* (I did nothing else aside meeting him)
- *I met only him on the train last night* (I did not meet anyone else on the train)
- *I met him only on the train last night* (I didn't meet him outside the train)
- *I met him on only the train last night* (I didn't meet him anywhere else)
- *I met him on the only train last night* (There was no other train except the one I met him on)

- *I met him on the train only last night* (It was only last night, not any other day)
- *I met him on the train last night only* (I have not met him before and most likely don't plan to meet him again)

Expert use of modifiers can greatly enhance communication and make affective communication so much clearer.

2.6 Mixing Metaphors and Modifiers: A Theoretical Analysis

As discussed in the previous section, the skilful use of modifiers adds flavour to a piece of text in discourse, whether written or spoken, and so it becomes likely that a speaker will use both metaphors and modifiers in their communication. It also then stands to reason that since metaphors greatly help in communicating affect, and modifiers add colour, the use of metaphors and modifiers together will produce a highly affective communication of emotion. It is crucial to note that metaphors are a classic way of conveying emotion. For instance, there has been a large amount of work done in the role of imagery in metaphoric communication, and a common idea has been how metaphors often appeal to the visual senses in such communication. Let us consider an example

Thomas was swimming in a sea of sorrow.

The use of *sea* paints a picture of a large expanse of water in which one can easily be overcome, or drown in. The sea is known for high and strong waves as well as turbulence that is enough to wreck ships of varying shapes and sizes. When people are lost at sea, it becomes almost impossible to find them. When a person is said to be swimming in the sea, relatively, that person is just a speck in an expanse of water. If that water is sorrow, then we get the idea of someone so lost in sorrow that there is little to no hope of redemption, and of someone whose life is very likely about to end for the sheer magnitude of sorrow that the person is faced with.

2.6.1 Mixing Metaphors and Modifiers: The Structure

Taking into consideration the various types of modifiers and how their placements are subjective according to the initiator of the discourse, albeit in a manner that does not break syntactic rules, let us consider an example, and analyse the many different ways in which modifiers can be placed, and how many could be considered as too many, being conscious of the fact that we do not want to confuse the participants of the communication.

Let us consider an example like

Her house was a prison.

I could add several modifiers in an attempt to enhance the interpretation of the metaphor by modifying the meaning of the object term as follows

Her house was a dark prison

Her house was a stinking, dark prison

The characteristics of a *prison* would include heavy doors, small cells, small and restrictive areas, lack of freedom of movement, being held there as a form of punishment, surrounded by high walls and other features to prevent escape, equipped with motion sensors, has roving patrols, has armed guards, has shared amenities, etc. It would appear that, the more modifiers that are added to the vehicle, the clearer the specific attributes that are teased out for mapping to the tenor. Adding the modifier *dark* would give a clearer characteristic of, for instance, just how oppressive this prison is in terms of restricted movement, and the light-sapping and agonizing element of dehumanized living. Adding the modifier *stinking* to all this, further enhances the picture by adding an element of disgust and the notion of a place where a typical human being would not want to be. I could also add a number of modifiers to the subject of this sentence and have statements like

Her green house was a prison

Her green house behind the market was a dark prison

Her green house behind the market was a stinking, dark prison.

Further examples of the use of modifiers in metaphors would be as follows, with the modifiers underlined:

Example 1:

Isaiah is a wolf in sheep's clothing.

Isaiah is a <u>wicked</u> wolf in sheep's clothing.

Isaiah is a <u>desperately wicked</u> wolf in sheep's clothing.

Isaiah <u>the American</u> is a <u>desperately wicked</u> wolf in sheep's clothing.

Isaiah <u>the tall American</u> is a <u>desperately wicked</u> wolf in sheep's clothing.

Example 2:

Amelia is a pain in the neck.

Amelia is a <u>nagging</u> pain in the neck.

Amelia is a <u>seriously nagging</u> pain in the neck.

Amelia the assistant is a seriously nagging pain in the neck.

Amelia the personal assistant is a seriously nagging pain in the neck.

Amelia, the personal assistant to the CEO, is a seriously nagging pain in the neck.

Example 3:

The idea was buried in his mind

The idea was buried in a corner of his mind

The idea was buried in a distant corner of his mind

The idea was buried in a dark and distant corner of his mind

The idea was deeply buried in a dark and distant corner of his mind

The brilliant idea was deeply buried in a dark and distant corner of his mind

The extremely brilliant idea was deeply buried in a dark and distant corner of his mind

2.6.2 Mixing Metaphors and Modifiers: The Results

This section will address what is achieved by mixing metaphors and modifiers. With the background knowledge that modifiers are sometimes added to sentences to make them more colourful in many different ways, a phenomenon that comes into play would be adding modifiers to metaphors merely in order to create an aesthetic effect. Johnson et al (1974) however suggested that adding modifiers to metaphors somehow reduce the power of their effectiveness in communicating their intended meanings, as these modifiers tend to break up the "integrity" of the metaphor by reducing the similarity between constituent nouns (the source and the target). From Johnson's (1970) theory of feature combination however, the additions of modifiers to nouns are expected to make more salient, a set of potential features which are appropriate to the unmodified noun, and that the modifier's effect should depend on whether they serve as intensifiers or downtoners in relation to the similarity mapping.

Let us consider an example like *The idea was buried in a corner of his mind*, which stems from the general conceptual metaphor of *Ideas as physical objects* (Lakoff and Johnson, 1980; page 47), I can insert a modifier that will add a bit more information to the burial place of the idea, in which case I can have

The idea was buried in a distant corner of his mind

In this example, three key sections give this metaphoric sentence its meaning – the idea to be buried, the distance involved which serves as the modifier, and the object which is the corner of his mind.

The definition of *corner* describes a physical space that is remote, obscure and not easily accessible. *Distant* also has definitions that show a type of separation that is far apart. *Distant* therefore intensifies the inaccessibility of the *corner,* and gives a picture of a *remote area that is located far away* in the mind, which is where the idea is not simply there in plain sight, but has also been *buried* (which itself means to be completely covered from sight). Technically, even though the mind is a physical part of the body, there is no literal corner in which an idea can be physically placed, much more dig a trench and bury that idea in, and this non-literalness is what essentially identifies the sentence as metaphorical.

Let us consider a context in which *Adam was made to walk the plank* is being used in a metaphoric sense. According to the Oxford dictionary, a plank is a "a long narrow flat piece of wood that is used for making floors, etc." and so in this situation, there is nothing literal about walking on a plank – nobody in their right sense is expected to take a walk on a piece of wood when there is plenty room on the ground. To *walk the plank* was used in the past as a form of punishment, where a board was placed over the side of a ship, and the person being punished is made to walk along that board with the ultimate aim of them falling into the sea. I could introduce a modifier, *narrow,* into this sentence and have the modified version reading

Adam was made to walk the narrow plank

Even though there is nothing literal about the plank, modifying it deepens the notion of difficulty that the person doing the walking is facing. I can further enhance this meaning by adding another modifier, *long* as follows:

Adam was made to walk the long, narrow plank

which makes the difficulty even more pronounced. Now the person is not simply walking to his death, but has to balance himself on a narrow plank, and has to walk a much longer way, which only lengthens his agony of the knowledge of impending death. I could further enhance this agony, by adding a word *excruciatingly* which explicitly addresses the walker's emotional state:

Adam was made to walk the excruciatingly long and narrow plank

At this point, there is no doubt that the person walking to his death is under a lot of stress, both emotionally and physically. The introduction of modifiers has indeed enhanced the overall picture created by the metaphor.

In another example,

It was a stormy meeting

this paints a picture of a storm in the mind's eye, extracts the attributes of a storm which includes *being marked by significant disruptions to normal conditions, strong winds, tornadoes, hail, thunder and lightning, strong winds or cyclones*. These attributes have negative valence, and so present a storm as a not so-positive thing as it can end with a lot of damage and destruction to property, debris and garbage being littered all over an area, people and animals being hurt, or even death to living things. Superimposing some of these attributes on a meeting, which is essentially an assembly of people for a specified purpose, usually a formal discussion, will paint the picture of a gathering of people with a lot of chaos, and possible having elements being thrown across the room as would typically happen in a storm. By extension, it could also depict a level of unhappiness and a hint of aggression.

Assuming I added a modifier like *very* which is also an intensifier, I get a statement that reads

It was a very stormy meeting

This does not change the basic meaning of the sentences in that, it is an unhappy and aggressive kind of a meeting, but the intensity of the emotions surrounding that meeting gets raised. The introduction of the modifier does not interpret the metaphor, but, the picture that was created in the first sentence becomes better explained. The modifier ***very*** directly affects the word ***stormy***, which both go to modify the emotions surrounding the meeting

On the other hand, if I choose to use a downtoner like *hardly*, I end up with a statement that reads

It was hardly a stormy meeting

This, on the contrary, minimises the negativity of the metaphor that was created at the first instance. The downtoner does its work as it is expected, and tones down the valence of the sentence under consideration.

Let us consider the negation of this metaphor in usage

It was not a stormy meeting

An obvious question that may arise during interpretation will be that if *It was not a stormy meeting*, why not just say *It was a meeting*? Categorically stating that it was *NOT* a stormy meeting may serve a purpose in the overall scenario in question. It could even be that earlier meetings had been stormy, and so the emphasis of the storm being absent in this particular meeting under review, is a sort of an achievement that is worth mentioning, but then again, all this will be entirely dependent on the scenario under consideration.

Adding an intensifier to the negation of the metaphoric sentence will give us a sentence which reads

It was not a very stormy meeting

This, from comprehension, will imply that there have or are meetings that are stormier than the one in question. It was stormy with all the characteristics of a storm and an overall negative valence, but it is not as negative or as wildly stormy as it might or could have been.

Using a downtoner on the negation of the metaphor sentence gives us a statement that reads

Relatively, it was not a stormy meeting.

Relatively will be comparing the current stormy meeting to previous stormy ones, and it comes up with the conclusion that even though this is stormy, it's child's play.

Other variants (the variations being the results of using different modifiers) of *It was a stormy meeting* will include the following:

It was a somewhat stormy meeting

It was a dangerously stormy meeting

It was a pleasantly stormy meeting

It was a pretty stormy meeting

It was an ugly, stormy meeting

2.7 Oxymorons

The oxymorons considered in this study are the ones that result from modifiers modifying words that are opposite in meaning to them. An oxymoron can be described as a figure of speech in which two opposing ideas are joined to create an effect. The simple oxymoron phrases consist of an adjective, adverb, modifier or a modifier in our case, followed by its antonym. Some examples of oxymorons will include *arrogant humility*, *alone together*, *ordered chaos*, *a little big*, *living dead*, *cruel kindness*, *original copy* and *virtual reality*. Though the definitions state that the joined words are of opposing meanings, it must be noted that there are several varying degrees of lexical contrast, which are mostly intuitively recognized by native speakers of any particular language. For example, *white* and *black* exhibit a higher degree of contrast than *white* and *grey*. Mohammad et al (2013) argue that being able to determine lexical contrast is crucial for analysing and solving a number of sentiment-related problems, though it may not, by itself, be enough to solve them. A number of computational approaches have been proposed for semantic closeness (Curran 2004; Budnitsky and Hirst 2006; Hearst 1992, Kagan 1984; Deese 1965), but measuring lexical contrast has been less successful. With the use of lexical databases in computing semantic closeness, a predefined word hierarchy is used, and this considers the word, its meaning, and its relationship with other words. These are stored using a tree-like structure (Li et al, 2006). When similarity is being checked, the methodology considers the path distance between the two words relative to the root node of the words. WordNet has the advantage of its internal structure being a close simulation of human recognition behaviours, and so with its tree-like representation, the Dijkstra's algorithm is suited for finding the similarity between words. The algorithm finds the shortest path between any two nodes, using the formula $\Theta((|V| + |E|)\log|V|)$ where $|V|$ is the number of nodes and $|E|$ is the number of edges.

Pawar and Mago (2018) proposed a system that was to improve existing methodologies used in computing semantic closeness as stipulated by Islam and Inkpen (2008), and Li et al (2006). Table 1 lists a subset of their final similarity values. The differences can be attributed to the methodologies they used in their computation of word similarity.

Table 1: Similarity Indices for three systems

S/N	WORD PAIR	Islam and Inkpen (2008)	Li et al (2006)	Pawar and Mago (2018)
1	Magician – Wizard	0.34	0.65	0.998
2	Cock - Rooster	0.94	1	0.909
3	Midday - Noon	0.93	1	0.999
4	Gem – Jewel	0.65	0.83	0.817
5	Automobile – Car	0.52	0.64	0.818
6	Cushion – Pillow	0.29	0.66	0.815
7	Boy – Lad	0.6	0.66	0.909
8	Bird – Woodland	0.12	0.33	0.165
9	Boy – Rooster	0.16	0.53	0.090
10	Cord – Smile	0.06	0.33	0.089
11	Autograph – Shore	0.11	0.29	0.074
12	Asylum – Fruit	0.07	0.21	0.072
13	Hill – Mound	0.15	0.74	0.814
14	Cord – String	0.45	0.68	0.814
15	Grin – Smile	0.32	0.49	0.991

Source: Pawar and Margo, 2018.

From their analysis, as with other systems, the greater the similarity index, the closer the similarity, implying that those words are synonyms. There is however no correlation between very small similarity indices and contrast which would have indicated the possibility of those words being antonyms, and this is illustrated in the cases of *boy* and *rooster*, *autograph* and *shore,* and *cord* and *smile*.

A classic example from literature is by William Shakespeare (1997) in *Romeo and Juliet*:

> *Why, then, O brawling love! O loving hate!*
> *O anything, of nothing first create!*
> *O heavy lightness! Serious vanity!*

Misshapen chaos of well-seeming forms!
Feather of lead, bright smoke, cold fire, sick health!
Still-waking sleep, that is not what it is!
This love feel I, that feel no love in this.
Dost thou not laugh?

In this piece, there is a series of oxymorons being employed when Romeo address the love of a woman who appears to be inaccessible to him. The effect of these oxymorons is to highlight his intense emotional and mental conflict through the use of contradictory word pairs like *loving hate, chaos of well-seeming forms, feather of lead, heavy lightness, bright smoke, cold fire* and *sick health, waking sleep*.

For the purposes of our work, therefore, I rely on the MacMillan thesaurus for antonyms to chosen words, as well as our intuitive antonyms and the corresponding senses as laid out in WordNet 3.0.

Let us consider the following sentence:

That Persian rug is ugly.

Ugly is a word that can intuitively be classified as having a negative connotation, and so using a modifier like *very* will increase the valence of *ugly* in the resulting sentence

That Persian rug is ***very*** *ugly*

I could alternatively have the sentence

That Persian rug is ***beautifully*** *ugly.*

The word ***beautifully*** acts, as a modifier in this case, but also happens to be an antonym of the word *ugly*, and results in an oxymoron *beautifully ugly*.

Antonyms for *ugly* include *pretty, beautiful, nice, pleasing, agreeable, attractive, delicate, gentle, good, kind, lovely, pleasant* and *safe.*

Considering the co-occurrence of two other words – *same* and *difference*, the definitions from WordNet of *same* include

- *Same in identity*
- *Closely similar or comparable in kind or quality or quantity or degree*
- *Equal in amount or value*
- *Unchanged in character or nature*

and the definitions of *difference* include

- *The quality of being unlike or dissimilar*
- *A significant change*

Having these two words together, with *same* qualifying *difference*, will produce an oxymoron since they are words of opposite meanings that have been placed side by side. *Same difference* can be used in a situation where a person desires to imply that two things that are intrinsically dissimilar produce effects that are so close to each other that the difference is negligible. A sample piece of text can be

> *If you were to ask me about the pros and cons of the NDC or the NPP, my honest opinion would be 'same difference'. Though they are political parties on opposing ends, my experience with them has not been any different on many levels.*

2.8 Affect

Affect is a very general term that includes several psychological phenomena that relate to feelings, and researchers have typically classified these feeling states into moods and emotions. Lazarus (1991) comments that moods can be distinguished from emotions by the inability to pinpoint a contextual provocation in the mood. He stated also that most moods are apparently not connected to a single object or piece of business, as is the case with acute anger or fear. He explains that when a person is either melancholy or cheerful, it is mostly impossible to identify the specific object that is the target for the anger, or the cause of the state. He concludes that moods are therefore larger and longer lasting, while emotions tend to be easily diffused and short-lived.

Emotion has been categorised into two very broad concepts – dimensional (e.g., Russell and Feldman Barret 1999; Russel 1980) and discrete categorical (e.g., Lazarus 1991; Shaver et al. 1987). Considering the dimensional approach, emotions are treated as a phenomenon that varies along a single dimension and ranges from positive affect to negative affect, or as a two-dimensional space that constitutes pleasure and arousal, and which ranges over a pleasant-unpleasant spectrum. When considering the discrete categorical view, emotion is seen as a set of distinct states that include fear, anger, sadness and happiness. These vary in intensity and manifest in different distinct patterns of changes in physiology (e.g., heartbeat), subjective consciousness (e.g., alertness) and behavioural readiness (e.g., to quarrel).

One of the common properties of the affective state or experience, whether in consideration of mood or emotion, is the valence, which is the perceived degree of positivity or negativity of the feeling. It is possible for a person to be in a good (positive) or bad (negative) mood, and experience a pleasant (positive, e.g., happy, excited) or unpleasant (negative, e.g., fear, anger) emotion. Thus, throughout the rest of this work, affect is taken as a general term, and one of its key characteristics is the valence.

2.9 Reporting Sentiment versus Expressing Sentiment

An issue that has not been of much emphasis in sentiment analysis is the issue of whether the total sentiment extracted from a piece of text is the writer's sentiment towards something, or it is the sentiment expressed by the scenario the writer is writing about. It becomes possible to have a perfectly objective and sentiment-free report of someone being angry, but then, also have a statement about someone being angry which expresses the writer's emotion about that situation. A writer could be sad, angry, amused, mocking, ashamed or even surprised about the anger being expressed.

Let us consider the following simple sentence:

1. *Emil was angry about Adel's appearance.*

This is a matter-of-fact, objective report (*reporting*) on Emil's sentiment (anger) towards Adel's appearance. The writer can however modify this statement to reflect his own sentiment (*expressing*) about the sentiment being expressed in the scenario, and so I could have a statement like

2. *To my uttermost dismay, Emil was angry about Adel's appearance.*

Transforming statement 1 into a metaphor, I could have a sentence like

1a. *Emil erupted like a volcano at Adel's appearance.*

This metaphoric statement is one that reports the scenario without including the writer's sentiment. The metaphoric version of the expression case which captures the writer's own sentiment in addition to reporting the sentiment from the scenario under discussion could read

2a. *I was thunderstruck when Emil erupted like a volcano at Adel's appearance.*

It is possible in discourse, and often preferred, that a writer or initiator of a conversation, gives some information about his thinking and emotional state at the time of communication. This would mean the writer *expressing* his sentiment about a particular topic or scenario. The person can achieve this by the choice of words used and the organization of the text. As an example, a person can present one event as either a glorious one or a totally horrible one through the choice of words used, even though the core events (who, what, when, where, how) may remain the same. An example could be

Sadly, the vase fell from his hand as he tripped on the carpet.

A different choice of words (like synonyms) may significantly affect the evaluation of the affect of a sentence. The sentence can now read as

To my uttermost horror, the priceless vase came flying out of his hand as he tripped on the carpet!

On the other hand, a writer who is objectively describing a scenario can use a mix of words to convey the affect of that scenario, in which case, the sentiment to be deduced would be solely based on the scenario in question, and totally devoid of the writer's sentiment. The sentence in this case could be written as

The vase fell from his hand as he tripped on the carpet.

This would be the writer *reporting* a sentiment.

Affect could also include a notion of *evaluation* in which a simple valence system could be employed to determine the overall polarity of a statement. Polanyi and Zaenen (2006) however argue how the use of such a valence system which uses the polarity of individual words in a text, is somewhat crude, and therefore not enough to conclude on the overall attitude of a discourse. They used three sentences in their argument (relevant terms are bold, positive terms are marked with a +, negative terms are marked with a -, and comparable neutral terms are underlined):

Text 1. The ***eighteen-year-old walked*** through the ***part of town where he lived***. He ***stopped for a while*** to ***talk*** with people on the street and then ***went*** to a store for some ***food*** to bring to the ***small apartment*** where he ***lived*** with some ***people he knew***.

Text 2. The ***young man***$^{+}$ ***strolled***$^{+}$ through ***his neighbourhood***$^{+}$. He ***lingered***$^{+}$ to ***chat***$^{+}$ with people on the street and then ***dropped into***$^{+}$ a ***shop***$^{+}$ for some ***goodies***$^{+}$ to bring ***home***$^{+}$ to the ***cozy***$^{+}$ place which he ***shared***$^{+}$ with some ***friends***$^{+}$.

Text 3. The ***teenaged male***$^{-}$ ***strutted***$^{-}$ through his ***turf***. He ***loitered***$^{-}$ to ***shoot the bull***$^{-}$ with people on the street and then ***ducked***$^{-}$ into a ***dive***$^{-}$ for some ***grub***$^{-}$ to bring to the ***cramped hole-in-the- wall***$^{-}$ where he ***crashed***$^{-}$ with some ***cronies***$^{-}$.

While all three statements present basically the same picture in terms of who, where and how, the affective evaluation of each version is different. In the first text, the protagonist is an unremarkable young man, in the second he is a much warmer and friendlier chap, and in the third, he is an outright juvenile delinquent.

There are some English words that can readily be tagged as either having a positive (examples include *delightful, happy, admire, amazing, celebrated*) or negative (examples include *angry, corrosive, cruel, disgusting, faulty*) valence, but it is worth noting that not all words can be easily tagged as such: many terms are basically neutral (examples include *different, same, selective, use, filled*). The valence of some words may also depend on context; in particular, the word may have more than one meaning, and each meaning could have a different valence. For example:

- *Wound,* which means *the past tense of wind* (neutral), or *to injure* (negative).
- *Row,* which means *line* (neutral); *an argument* (negative), or *to propel a boat* (neutral to positive).
- *Learned,* which means *past tense of learn* (neutral), or *knowledgeable* (positive).
- *Fine,* which means *of good quality* (positive), or *a levy* (neutral to negative).
- *Entrance,* which means *the way in* (neutral), or *to delight* (positive).

A sentiment analysis system should therefore be able to distinguish between these two sentiments, and be able to represent them appropriately, and determine which of the two sentiments is more preferred – the sentiment within the scenario (the reporting type), or the sentiment of the one writing about the scenario (the expression type).

2.10 Chapter Summary

This chapter does an in-depth study of the three main themes of the research – metaphors, affect and modifiers. It examines the various types of metaphors, how they are identified in language, both manually and automatically. It also examines sentiment, the various categories of sentiment and machine learning approaches to sentiment analysis. I go on to explain the relationship between metaphors and affect, and how affect impact the understanding of metaphors. I then look at adverbs and how incorporating them into metaphors impact the meaning and affective communication. I go on to examine oxymorons as a result of mixing modifiers that are opposite in meaning.

CHAPTER THREE

RESEARCH METHODS

3.1 Introduction

Du Bois (2007) states that evaluative language involves indexing the act of evaluation or that of stand-taking, and Hunston (1994) further explains that this helps in expressing an attitude towards a person, situation or any other entity that could be subjective as well as located in a societal value-system.

Evaluation could be subjective as it may reflect the sentiment of the writer or speaker, and is strengthened by intensifiers like *very, thoroughly* and *truly*. The ability to differentiate between the subjective sentiment of the writer, and the objective point of the scenario under study, depends on an understanding of the nature of the evaluation. This understanding can be made possible by the study of the lexical resources that are used to carry out the evaluation, namely words, collocations and phrases, and as recommended by Stubbs (1986), has been in extensive use in evaluating literature on metadiscourse, stance and engagement (Biber, 2006a; Hyland, 2009; Hyland and Tse, 2004). Another way of evaluation, which has been adopted by researchers like Taboada and Grieve (2004), involves identifying positive and negative evaluations (using automatic identification on evaluative language) in very large collections of texts. Even though adjectives and adverbs (which are part of our set of modifiers) usually express evaluative meanings (Turney, 2002; Conrad and Biber, 2000), they are not the definite markers for evaluation.

Corpus linguistics covers a very wide range of activities and approaches (e.g. Teubert, 2005; Sampson and McCarthy, 2005; Baker, 2009), and at its most basic definition, is concerned with the collection of some quantities of electronic text for data manipulation techniques (McEnery & Hardie, 2011). This is not to say that it is a set of simple data analysis techniques – it is much more than that. It is a complex field which blends technological advancement and theoretical development, for example, analysing the text in the immediate neighbourhood of a pivot word in order to highlight similarity or otherwise in context.

Frequency analysis is also commonly used in corpus linguistics to aid in extracting sentiment or carrying out text categorization. Without a doubt, full-body text (a term I use to refer to whole documents as opposed to phrases or single sentences) for any such task will be the best for information representation of meaning as this will capture many differing sentiments that may be expressed at different levels, be they the writer's sentiments or the sentiments of the scenario under consideration. However, using such a large repository of full-body text can hinder the extraction of sentiment because of the complexity of language due to the use of literary devices like metaphors and oxymorons. Frequency analysis typically generates a ranked list of word tokens, each token being a single word, a cluster of words consisting of bigrams and trigrams, or unigrams which may be composed of a mixture of upper and lowercase alphabetic characters.

Even though key word in context (KWIC) analysis is also very suitable in determining the context of pieces of text, it will not be used in our research. This is due to the fact that there is a vast diversity of metaphors ranging from dead to novel metaphors, and it becomes illogical to attempt looking for the company of words that a particular metaphorically-used word keeps.

In this research, I will attempt to use very basic forms of evaluative language and corpus linguistics by examining the lexical units of phrases and sentences with the aim of extracting sentiment information. I will use the python programming language and VADER, which is its inbuilt sentiment analyzer, WordNet 3.0 and SentiWordNet 3.0. I will also use the ItenCheck app, the MonkeyLearn app as well as the Free Sentiment Analyzer, which are all existing Sentiment Analysis systems, to see how they fare in analysing metaphors and oxymorons. I shall also be using libraries like the British National Corpus (The British National Corpus, 2007) hereafter referred to as the BNC, and the Corpus of Global Web-based English (Davies, 2013) hereafter referred to as GloWbE, which allows us to cover different dialects of the English language.

3.2 The British National Corpus

The British National Corpus (XML Edition, 2007) is a 100-million-word collection of samples of written and spoken language from a wide range of sources, and is designed to represent a wide cross section of British English from the later part of the 20th century. The written portions, which constitute 90% of the BNC, includes extracts from both regional and national newspapers, specialist periodicals and journals that cover all age ranges and diverse interests, both academic books and popular fiction, as well as published and unpublished letters and memoranda. It also includes school and university essays, as well as other kinds of text. The spoken part constitutes the remaining 10% and is made up of transcriptions of unscripted informal conversations as well as spoken language that has been collected in different contexts and which range from formal business or government meetings to radio shows. It is monolingual and deals with modern British English only, but has some non-British English and some foreign language word occurring in the corpus.

3.3 GloWbE

The Corpus of Global Web-based English (GloWbE – Davies, 2013) is a 1.9-billion-word corpus which includes words used in English discourse from 20 different countries including Great Britain, United States, Australia, Ireland, India, Sri Lanka, Tanzania, Ghana, Jamaica and Canada. The texts consist of informal blogs, which forms about 60% of the corpus, and other web-based materials including magazines, company websites and newspapers among others. The constituents of GloWbE according to countries and their corresponding number of websites, webpages and words are listed in Table 2.

3.4 The Python Programming Language

Python is an interpreted, general purpose, high-level and open source programming language which is very simple and easy to use, and used in a lot of cases for developing desktop graphical interfaces, web applications and websites. It has great capability for using libraries such as those that have been used in this research, and so provides a great programming interface for experiments that have been carried out here. Python uses an interpreter as opposed to a compiler and so executes the program code directly on the system.

For ease of use, the Integrated DeveLopment Environment (IDLE) platform which gives access to a python shell window that is interactive, and the terminal have been used throughout this report. The python editor, Sublime, proved difficult to use because of the libraries that needed to be imported.

Table 2: Constituents of the GloWbE Corpora

Country	Web sites	Web Pages	Words
United States	82,260	275,156	386,809,355
Canada	33,776	135,692	134,756,381
Great Britain	64,351	381,841	387.615,074
Ireland	15,840	102,147	101,029,231
Australia	28,881	129,244	148,208,169
New Zealand	14,053	82,679	81,390,476
India	18,618	113,765	96,430,888
Sri Lanka	4,208	38,389	46,583,115
Pakistan	4,955	42,769	51,369,152
Bangladesh	5,712	45,059	39,658,255
Singapore	8,339	45,459	42,974,705
Malaysia	8,966	45,601	42,420,168
Philippines	10,224	46,342	43,250,093
Hong Kong	8,740	43,936	40,450,291
South Africa	10,308	45,264	45,464,498
Nigeria	4,516	37,285	42,646,098
Ghana	3,616	47,351	38,768,231
Kenya	5,193	45,962	41,069,085
Tanzania	4,575	41,356	35,169,042
Jamaica	3,488	46,748	39,663,666
TOTAL	340,619	1,792,045	1,885,632,973

Source: Davies, 2013

3.5 WordNet

According to Princeton University (Princeton University, 2010), WordNet® is a large lexical database of English in which nouns, verbs, adjectives and adverbs are grouped into sets of cognitive synonyms (synsets), each expressing a distinct concept. It is the most commonly used resource for English sense relations (Fellbaum,1998) and contains three databases one each for nouns and verbs, and a third for adjectives and adverbs. It has lexical categories and the synonyms of words, as well as semantic relations between the different words or sets of words. It represents relations between senses using hypernyms and hyponyms, meronyms and holonyms, entailments, and word similarity, and includes glosses that are definitions for senses in the text string format. The major relation among words in WordNet is synonymy, as exists between the words *look* and *see*, or *hate* and *detest*. Synonyms are words that denote the same concept and can be used interchangeably in many contexts. Word forms that have several distinct meanings are represented in as many distinct synsets, thus, creating a whole list of unique form-meaning pairs. The following are noteworthy in relation to the implementation of WordNet in Python:

3.5.1 Synonyms

Synonyms are stored in WordNet in the form of synsets. A synset is a group of synonyms that are considered to be equivalent in terms of their meanings (or semantics). They are words that qualify to be used interchangeably in some contexts while maintaining the truth-values of the sentences within which they occur. Each synset has an associated definition, and there are relations stored between the different synsets. As an example, there are two synsets corresponding to the word 'apple' and these are 'apple.n.01' and 'apple.n.02'. The first has definition '"fruit with red or yellow or green skin and sweet to tart crisp whitish flesh" and the second has definition '"native Eurasian tree widely cultivated in many varieties for its firm rounded edible fruits".

3.5.2 Hyponyms and Hypernyms

Simply put, Hyponyms and Hypernyms are specific and generalized concepts respectively. The first noun sense of *love* has 12 hyponyms, meaning there are 12 different synsets that are examples of the noun *love*, while the hypernym of the same is only 1 – *emotion*.

As an example, the hyponyms of the first noun sense of love are listed as

- *agape.n.01*
- *agape.n.02*
- *amorousness.n.01*
- *ardour.n.02*
- *benevolence.n.01*
- *devotion.n.01*
- *filial_love.n.01*
- *heartsrings.n.01*
- *lovingness.n.01*
- *loyalty.n.02*
- *puppy_love.n.01*
- *worship.n.02*

The hypernym of the first noun sense of love however, is *emotion.n.01*.

3.5.3 Meronyms and Holonyms

These represent the part/whole relationship with meronym representing the part while the holonym represents the whole. As a typical example, an *eye* is meronym of *face* and *visual system* while *hand* is a holonym of *fingernail.*

3.5.4 Entailments

An entailment means a deduction or an implication, which is to say that something follows logically from, or is implied by something else. For example, *breathe* entails *exhale* and *inhale.*

3.5.5 Word Similarity

One of the proposed ideas for evaluating the similarity between words is the Quilian's Semantic Memory Model (Quilian, 1968), which uses the number of hops between the nodes of concepts (more familiarly, synsets) in the hierarchical network to quantify similarity or difference of the concepts (synsets). Wu and Palmer (1994) also calculated semantic similarity based on the path length between synsets located in a taxonomy in addition to the depth of the Least Common Subsumer (LCS). The formula is

$$score = 2*depth(lcs) / (depth\ (s1) + depth\ (s2))$$

where ***s1*** and ***s2*** are the words being compared.

For example, in comparing ***cancer*** and ***disease***

Lowest Common Subsumer(s) = argmax(depth(subsumer(T1,T2))) = { subsumer(T1[2], T2[1]) } = disease#n#1 }

DepthLCS *= depth (disease#n#1) = 11*

$$Depth1 = min(depth(\{tree\ in\ T1 \mid tree\ contains\ LCS\ \})) = 14$$

$$Depth2 = min(depth(\{tree\ in\ T2 \mid tree\ contains\ LCS\ \})) = 11$$

$$\boldsymbol{Score} = 2 * DepthLCS / (Depth1 + Depth2) = 2 * 11 / (14 + 11) = 0.88$$

The shorter the distance (the closer to 1 the value), the more similar the words are. Thus, it becomes possible to quantitatively conclude that a *flask* and *grass* are 38% similar (their score is 0.3809,) while a *goat* and a *sheep* are 94% similar (their score is 0.9375). This research uses the Wu and Palmer (1994) method within the python framework.

3.6 SentiWordNet

Even though there have been various issues raised with the simple computation of polarities of pieces of text by simply finding the polarities of individual words and finding an average, as discussed in the background studies, it still seems to be a useful approach for some purposes. This usefulness is greatly enhanced by the use of SentiWordNet. SentiWordNet (version 3.0) is an enhanced lexical resource for opinion mining and sentiment analysis in which each WordNet synset *s* is associated to three numerical score *Obj(s), Pos(s)* and *Neg(s)*, describing how objective (which means the same as neutral), positive and negative the terms contained in the synset are (Esuli and Sebastiani, 2006). These three scores are derived by combining the results produced by a committee of eight ternary classifiers, all characterized by similar accuracy levels but different classification behaviours.

Esuli and Sebastiani (2006) trained a set of ternary classifiers, each of which is capable of determining whether a synset is positive, negative or neutral.

Each of the classifiers was trained using a different training set, and if all the classifiers agreed on an opinion score, it was assigned to that synset as its maximum score. If the classifiers were not in agreement, the label for that synset consisted of a score proportional to the number of classifiers that assigned a particular sentiment to it. A list of synsets can be generated for a word using python, and so for a word like *slow*, I can have the following list:

- decelerate.v.01
- slow.v.02
- slow.v.03
- slow.a.01
- slow.a.02
- dense.s.04
- slow.a.04
- boring.s.01
- dull.s.08
- slowly.r.01
- behind.r.03

Each synset is made up of a word (e.g., 'boring'), the part of speech ('r' for *adverb*, 'a' for *adjective,* 'n' for *noun,* 'v' for *verb*, and 's' for *adjective*) and the sense number (e.g., '01'). For example, *slow.v.02* is the second verb definition of slow (*become slow or slower*) while the *slow.v.03(cause to proceed more slowly)* is the third verb definition for slow. The word sense 01 is considered as the primary sense. Synsets are used in SentiWordNet (based on WordNet) because there is an assumption that different sense of a term may have different opinion-related properties, which is evident only in its usage. For example, the synsets of *Happy* are

- 'happy.a.01' which means *enjoying or showing or marked by joy or pleasure*
- 'felicitous.s.02' which means *marked by good fortune*
- 'glad.s.02' which means *eagerly disposed to act or to be of service*
- 'happy.s.04' which means *well-expressed and to the point*

and these individual lemmas will have different sentiment scores given in Table 3.

Table 3: Sentiment Scores for Synsets of 'Happy' using SWN

Synset	Positive Score	Negative Score	Objective Score
happy.a.01	0.875	0.0	0.125
felicitous.s.02	0.75	0.0	0.25
glad.s.02	0.5	0.0	0.5
Happy.s.04	0.125	0.0	0.875

The scores in Table were extracted from SWN using the following python code:

from nltk.corpus import sentiwordnet as swn

count=0

while(count<5):

syns=swn.senti_synset(word) [e.g. of word here being *happy.a.01*]

syns.pos_score()

syns.neg_score()

syns.obj_score()

3.7 The Sentiment Classification Process

The afore-mentioned tools will be used altogether in the sentiment classification process that is illustrated by Figure 2. Each of these are briefly described in the subsequent sections

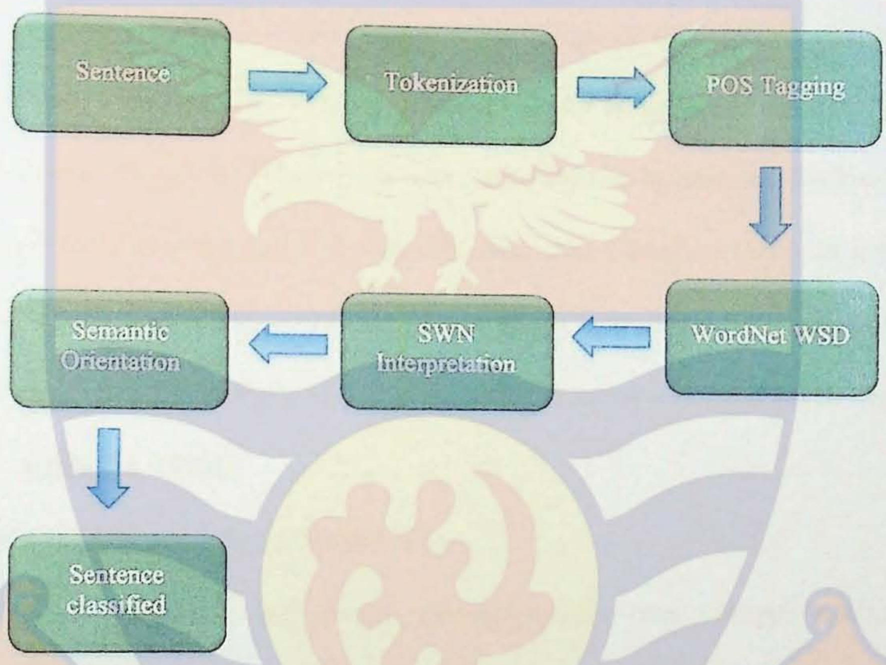

Figure 2: The sentiment classification process

3.7.1 Tokenization

This is the process of splitting a piece of text into the individual words (tokens) of the English language. Python has an inbuilt tokenizer that allows us to easily do this for even large pieces of text. For a sentence like "*The memory was lurking in a dark corner of her subconscious*", the tokens generated will look like

['The', 'memory', 'was', 'lurking', 'in', 'a', 'dark', 'corner', 'of', 'her', 'subconscious']

If I decide to carry out sentence-level analysis of a large piece of text, Python also has a function for splitting the text of the document under review into the constituent sentences to aid our analysis and so, a chunk of text like

> *Okonkwo was well known throughout the nine villages and even beyond. His fame rested on solid personal achievements. As a young man of eighteen he had brought honour to his village by throwing Amalinze the Cat. Amalinze was the great wrestler who for seven years was unbeaten, from Umuofia to Mbaino. He was called the Cat because his back would never touch the earth. It was this man that Okonkwo threw in a fight which the old men agreed was one of the fiercest since the founder of their town engaged a spirit of the wild for seven days and seven nights.* (Achebe, 1994)

can be broken down into a structure like

> *['Okonkwo was well known throughout the nine villages and even beyond.',*
> *'His fame rested on solid personal achievements.',*
> *'As a young man of eighteen he had brought honour to his village by throwing Amalinze the Cat.',*
> *'Amalinze was the great wrestler who for seven years was unbeaten, from Umuofia to Mbaino.',*
> *'He was called the Cat because his back would never touch the earth.',*
> *'It was this man that Okonkwo threw in a fight which the old men agreed was one of the fiercest since the founder of their town engaged a spirit of the wild for seven days and seven nights.'*]

3.7.2 Part-of-Speech Tagging

Part-of-Speech (POS) tagging presents various tags as an annotation to indicate the specific role that each token or word or lemma is playing in a sentence. Its significance in natural language processing is the large information it gives about a word and its neighbours. One of the things that POS tagging does is to give fine distinctions between the possessive pronouns (*my, your, his, her, its*) and the personal pronouns (*I, you, he, me*). Knowing this distinction helps in evaluating the kind of words that are likely to be in the neighbourhood. For example, possessive pronouns are very likely to be followed by nouns, and personal pronouns are likely to be followed by verbs (Jurafsky and Martin 2008). Again, a word's part-of-speech can indicate how they are pronounced, which is useful in speech synthesis systems to provide more accuracy in speech recognition. For example, the noun *OBject* is pronounced differently for the verb *obJECT*, the noun *DIScount* is pronounced differently form the verb *disCOUNT*, and the noun *CONtent* is pronounced differently from the adjective *conTENT*. POS can also play a major role in information retrieval since knowing the POS of a word can inform us of which morphological affixes it can take. An automatic assignment of POS helps with parsing, as well as word-sense disambiguation and quickly finding items like names or dates in information extraction applications.

Recent lists of parts-of-speech have had quite a number of word classes. For example, Penn Treebank (Marcus et al., 1993), shown in Table 4, has 45 tags. The Brown Corpus (Francis and Kučera, 1982) has 87, and the C7 tagset (Garside and Smith, 1997) has 146. Lancaster University's UCREL's

(University Centre for Computer Corpus Research on Language) C5 tagset laid out in the British National Corpus is shown in Table 5.

Python's NLTK library has its own tag set, shown in Table 6. A sentence

The memory was lurking in a dark corner of her subconscious

will be tagged using NLTK's library as

[('The', 'DT'),
('memory', 'NN'),
('was', 'VBD'),
('lurking', 'VBG'),
('in', 'IN'),
('a', 'DT'),
('dark', 'JJ'),
('corner', 'NN'),
('of', 'IN'),
('her', 'PRP$'),
('subconscious', 'JJ')]

Table 4: Penn Treebank Part-of-Speech Tags including Punctuation

Tag	Description	Example	Tag	Description	Example
CC	Coordin. Conjunction	*and, but, or*	SYM	Symbol	*+, %, &*
CD	Cardinal number	*1one, two, three*	TO	"to"	*to*
DT	Determiner	*a, the*	UH	Interjection	*ah, oops*
EX	Existential 'there	*there*	VB	Verb, base form	*ate*
FW	Foreign word	*mea culpa*	VBD	Verb, past tense	*ate*
IN	Preposition/sub-conj	*of, in, by*	VBG	Verb, gerund	*eating*
JJ	Adjective	*yellow*	VBN	Verb, past participle	*eaten*
JJR	Adj., comparative	*bigger*	VBP	Verb, non-3sg pres	*eat*
JJS	Adj., superlative	*wildest*	VBZ	Verb, 3sg pres	*eats*
LS	List item marker	*1, 2, one* `	WDT	Wh-determiner	*which, that*
MD	Modal	*can, should*	WP	Wh-pronoun	*what, who*
NN	Noun, sing or mass	*llama*	WP$	Possessive wh-	*whose*
NNS	Noun, plural	*llamas*	WRB	Wh-adverb	*how, where*
NNP	Proper noun, singular	*IBM*	$	Dollar sign	*$*
NNPS	Proper noun, plural	*Carolinas*	#	Pound sign	#
PDT	Predeterminer	*all, both*	"	Left quote	"
POS	Possessive ending	*'s*	"	Right quote	"
PRP	Personal pronoun	*I, you, he*	(	Left parenthesis	[, (, {, <
PRP$	Possessive pronoun	*your, one's*	)	Right parenthesis	],), }, >
RB	Adverb	*quickly, never*	,	comma	,
RBR	Adverb, comparative	*faster*	.	Sentence-final punc	. ! ?
RBS	Adverb, superlative	*fastest*	:	mid-sentence punc	: ; ... _ -
RP	Particle	*Up, off*			

Reference: Jurafsky and Martin, 2008

Table 5: UCREL's C5 Tagset for the British National Corpus

Tag	Description	Example
AJ0	Adjective (unmarked)	*good, old*
AJC	Comparative adjective	*better, older*
AJS	Superlative adjective	*best, oldest*
AT0	article	*the, a, an*
AV0	Adverb (unmarked)	*often, well, longer, furthest*
AVP	Adverb particle	*up, off, out*
AVQ	Wh-adverb	*when, how, why*
CJC	Coordinating conjunction	*and, or*
CJS	Subordinating conjunction	*although, when*
CJT	The conjunction *that*	*That*
CRD	Cardinal numeral (except *one*)	*3, twenty-five, 734*
DPS	Possessive determiner	*your, their*
DT0	General determiner	*these, some*
DTQ	Wh-determiner	*whose, which*
EX0	Existential *there*	
ITJ	Interjection or other isolate	*oh, yes, mhm*
NN0	Noun (neutral for number)	*aircraft, data*
NN1	Singular noun	*pencil, goose*
NN2	Plural noun	*pencils, geese*
NP0	Proper noun	*London, Michael, Mars*
ORD	Ordinal	*sixth, 77th, last*
PNI	Indefinite pronoun	*none, everything*
PNP	Personal pronoun	*you, them, ours*
PNQ	Wh-pronoun	*who, whoever*
PNX	Reflexive pronoun	*itself, ourselves*
POS	Possessive 's or '	
PRF	The preposition *of*	

PRP	Preposition (except *of*)	*for, above, to*
PUL	Punctuation – left bracket	*(or [*
PUN	Punctuation – general mark	*. ! , : ; - ? ...*
PUQ	Punctuation – quotation mark	*' ' " "*
PUR	Punctuation – right bracket	*) or]*
TO0	Infinitive marker *to*	
UNC	Unclassified items (not English)	
VBB	Base forms of *be* (except infinitive)	*am, are*
VBD	Past form of *be*	*was, were*
VBG	-ing form of *be*	*being*
VBI	Infinitive of *be*	
VBN	Past participle of *be*	*been*
VBZ	-s form of *be*	*is, 's*
VDB/D/G/I/N/Z	Form of *do*	*do, does, did, doing, to do, etc*
VHB/D/G/I/N/Z	Form of *have*	*have, had, having, to have, etc*
VM0	Modal auxiliary verb	*can, could, will, 'll*
VVB	Base form of lex. verb (except infin)	*take, live*
VVD	Past tense form of lexical verb	*took, lived*
VVG	-ing form of lexical verb	*taking, living*
VVI	Infinitive of lexical verb	*take, live*
VVN	Past participle form of lex. Verb	*taken, lived*
VVZ	-s form of lexical verb	*takes, lives*
XX0	The negative *not* or *n't*	
ZZ0	Alphabetical symbol	*A, B, c, d*

Source: Jurafsky and Martin, 2008

Table 6: NLTK's list of POS Tags

Tag	Description	Examples
CC	Coordinating conjunction	*and*
CD	Cardinal digit	*2, 3*
DT	determiner	*a, the*
EX	existential there	*There is …any form of "there exists"*
FW	Foreign word	
IN	Preposition/subordinating conjunction	*in, on, under*
JJ	adjective	*big*
JJR	Adjective, comparative	*bigger*
JJS	Adjective, superlative	*biggest*
LS	List marker	*1)*
MD	Modal could	*will*
NN	Noun, singular	*desk*
NNS	Noun plural	*desks*
NNP	Proper noun singular	*Harrison*
NNPS	Proper noun plural	*Americans*
PDT	Predeterminer	*"all" the kids*
POS	Possessive ending	*parent's*
PRP	Personal pronoun	*I, he, she*
PRP$	Possessive pronoun	*my, his, hers*
RB	Adverb	*very, silently*
RBR	Adverb, comparative	*better*
RBS	Adverb, superlative	*best*
RP	Particle	*up*
TO	To	*go 'to' the store*
UH	Interjection	*Errrrrmmmmm*
VB	Verb, base form	*Take*
VBD	Verb, past tense	*Took*

VBG	Verb, gerund/present participle	*Taking*
VBN	Verb, past participle	*Taken*
VBP	Verb, singular present, non-3d	*Take*
VBZ	Verb, 3rd person singular present	*Takes*
WDT	Wh-determiner	*Which*
WP	Wh-pronoun	*Who, What*
WP$	Possessive wh-pronoun	*Whose*
WRB	Wh-adverb	*Wehre, when*

Source: https://pythonprogramming.net/natural-language-toolkit-nltk-part-speech-tagging

3.7.3 WordNet Word Sense Disambiguation

In working with language processing, one of the interesting things is noticing just how ambiguous words are. It then becomes critical to be able to correctly interpret the words within the correct context of usage. Let us consider the word *bark*. WordNet gives 9 synsets, 4 of them being for noun senses and the remaining 5, verb senses. Assuming I wanted to use the *noun bark*, I have the following definitions

1. tough protective covering of the woody stems and roots of trees and other woody plants
2. a noise resembling the bark of a dog
3. a sailing ship with 3 (or more) masts
4. the sound made by a dog

and the ensuing sentences

1. The bark of the mahogany tree has medicinal properties
2. The dog's bark sounded like a wolf in distress

If a human is doing interpretation, it is obvious that the first sentence is using the word "*bark (of tree)*" as in the first sense, and the second sentence is using "*bark (of dog)*" as in the fourth sense. The difficulty then, is replicating this human ability.

NLTK has the Lesk Algorithm that estimates the sense of a word in a given context sentence. The algorithm assumes that words that are close together (or in a given 'neighbourhood') will very likely share a common topic. Using Lesk to try and disambiguate the word sense of 'bark' in the sentence *The dog's bark sounded like a wolf in distress,* I will have it returning the second noun sense of the synset *bark,* which is accurate in the sense of what is being referred to in that context. Passing it another sentence, *The bark of the mahogany tree has medicinal properties* returns the sense of *bark* in use as that of a dog's bark. In essence, Lesk is not accurate enough as it is sensitive to the exact wording of definitions, which makes it quite inflexible in its implementation, and also makes it prone to misrepresentations and misinterpretations. The absence of a certain word can totally flip the coin on the results. This flaw can be mitigated by improving the sense disambiguation in Lesk. An ability to obtain the correct context-free grammar and definitions would remove the rigidity of needing the exact word definitions, thereby reducing misinterpretations and misrepresentations. Due to this fact, the sense disambiguation carried out in this research is by manual inspection because I am considering a list of *n* words, making use of the senses as outlined in WordNet 3.0, and referencing the Macmillan dictionary as needed.

3.7.4 SentiWordNet Interpretation

Let us consider an example to illustrate the SentiWordNet interpretation:

I love pickles.

Because I want to eventually evaluate the sentiment score of the full sentence, I will need to first tokenize, which gives us

[('I', 'PRP'),

('love', 'VBP'),

('pickles', 'NNS')]

I then carry out a Word Sense Disambiguation using the Macmillan Dictionary and the sentiment scores laid out in SentiWordNet.

- I: This has been tagged as PRP (personal pronoun) and has no definition in WordNet.
- Love: The appropriate sense for *love* in this sentence which has been tagged as VBP (singular present tense of a verb) will be the first verb sense (love.v.01) and which means to have a *great affection or liking for* with an example being *I love French food.*
- Pickles: It is tagged as NNS (plural noun) and by manual inspection; the most appropriate definition will be the first noun sense (pickle.n.01) which is *vegetables (especially cucumbers) preserved in brine or vinegar.*

3.7.5 Semantic Orientation

Semantic Orientation (SO) is a measure of sentiment in text, which is mainly the measure of subjectivity. It measures how positive or negative the text is, and the degree to which the word, phrase, sentence or document is positive or negative towards the subject matter, person or idea (Osgood, Suci and Tannenbaum, 1957). In this research, sentiment analysis will be used in reference to the general methods of extracting polarity from text while semantic orientation will refer to the degree of polarity. The methodology used will be the lexicon-based approach which involves calculating the orientation of a piece of text by using the semantic orientation of words or phrases in that text, as laid out by Turney (2002). Quite a number of lexicon-based researches have focused on using adjectives as indicators of semantic orientation (Hatzivassiloglou and McKeown 1997; Wiebe 2000; Hu and Liu 2004; Taboada, Anthony and Voll 2006). In these approaches, a list of adjectives and their corresponding SO values are assembled into a dictionary so that for any piece of given text, these adjectives are extracted and scored using their SO values. These individual values are then aggregated into a single score and presented as the score for that whole piece of text.

As an example, let us consider our example sentence *I love pickles*. *I* has no synset in WordNet and by extension, SentiWordNet. *Pickles* has two synsets, but from the WSD, the sense I am using is the first noun sense to mean *vegetables (especially cucumbers) preserved in brine or vinegar*, which comes with an objective score of 1. I am also using the first verb sense of the word love, and the sentiment scores for these three senses are shown in Table 7.

Table 7: Sentiment scores to compute Semantic Orientation using SWN

Token	Pos_score	Neg_score	Obj_score
I	0.0	0.0	1.0
Love	0.5	0.0	0.5
pickles	0.0	0.0	1.0

These scores are then summed according to the polarities – all positive scores are put together, all negative scores are put together, and all objective scores are put together. Using the following notation

$$Sp = \sum_{i \in S} p\_score\ i$$

where S_p is the polarity being calculated, p_score is the polarity score of the word i in the sentence S, and i is the ith word in sentence S

I will have, for the positive score,

$$S+ = \sum_{i \in S} pos\_score\ i$$

and for the negative score,

$$S\_ = \sum_{i \in S} neg\_score\ i$$

and for the neutral score,

$$S * = \sum_{i \in S} obj\_score\ i$$

In computing the overall score, I will find the average of these summations which is given by

$$SAgv+ = \frac{(\sum_{i \in S} pos\_Score\ i)}{n}$$

and

$$SAvg\_ = \frac{(\sum_{i \in S} neg\_score\ i)}{n}$$

and

$$SAvg\_ = \frac{(\sum_{i \in S} neu\_score\ i)}{n}$$

for positive, negative and neutral scores respectively.

$$S = \begin{cases} positive\ if\ S+ > S\_, S* \\ negative\ if\ S\_ > S+,\ \ S* \\ neutral\ if\ S* > S\_,\ \ S+ \end{cases}$$

Using the values in Table 7 as an example:

Let *pos_score*, *neg_score* and *neu_score* but the scores for positive, negative and neutral respectively. *I* has an objective score of 1; *love* has a positive score of 0.5 and a neutral score of 0.5; pickles has a neutral score of 1. To find the semantic orientation of the sentence *I love pickles* therefore, average positive score is ((0+ 0.5+ 0)/3) = 0.166, average negative score is 0, average neutral score is ((1+0.5+1)/3) = 0.833. The statement therefore has a neutral polarity.

3.8 VADER

VADER (Valence Aware Dictionary and sEntiment Reasoner) is a lexicon and rule-based sentiment analysis tool that is specifically attuned to sentiments expressed in social media (Hutto and Gilbert, 2014). VADER works by computing the sentiment scores of some specified words (based on words that have been tagged as containing sentiment), and summarizes these individual scores into an aggregate. It has some subtle nuances built into it so that VADER is able to do classification slightly beyond the conventional bag-of-words method. These nuances include the rating of some contextual elements like punctuation, capitalization and modifiers.

For example, *She is beautiful* will have a lower score than *She is beautiful!!* and *Really?????* will have a higher emotional score than *Really?*. The VADER computation in this instance would take into consideration the number of exclamation marks or questions marks at the end of the sentence. Another heuristic that VADER considers is capitalization. *Delicious food* will definitely be less intense than *DELICIOUS food*, just as *Justin is ANNOYING* will be more intense than *Justin is annoying.* VADER does not implement any augmented scoring for words that are in bold or italics. Yet another heuristic is the annotation of degree modifiers. VADER uses a booster dictionary that contains a set of intensifiers and diminishers. Typical examples would include *She is extremely* pretty and *She is sort of pretty.* Another heuristic is the

consideration of shifts in polarity due to the use of *but*. This becomes important especially in cases where one sentence has mixed sentiments as in the case of *I adore you but I do not want to marry you.* Lastly, VADER uses trigrams (a set of three lexical features like "***I do not*** love football") occurring before a sentiment-laden lexical unit ("love" in this example) in order to detect polarity negation, and then multiply the sentiment lexicon's score by an empirically determined value of
-0.74.

VADER uses a dictionary that maps lexical features to sentiment scores, and the score is obtained by adding up all the emotion intensities of each word in the piece of text or sentence. The emotional intensities or sentiment score for each word was computed by averaging the ratings of a number of human raters from Amazon Mechanical Turk, and so relied heavily on the wisdom of the crowd. This was to eliminate the subjective error that could be introduced by different people viewing the same word in different sentimental light. Each word has an integer score between -4 to +4 (extremely negative and extremely positive respectively) with 0 being neutral, and the overall score of a sentence is between -1 and +1. In the python implementation of VADER, the sentiment of a sentence is achieved by applying a normalization represented by

$$\frac{x}{\sqrt{x^2 + \alpha}}$$

with x being the sum of the sentiment scores of the individual words in the sentence, and α being the normalization parameter, set to 15. The graphed normalization is shown in figure 3.

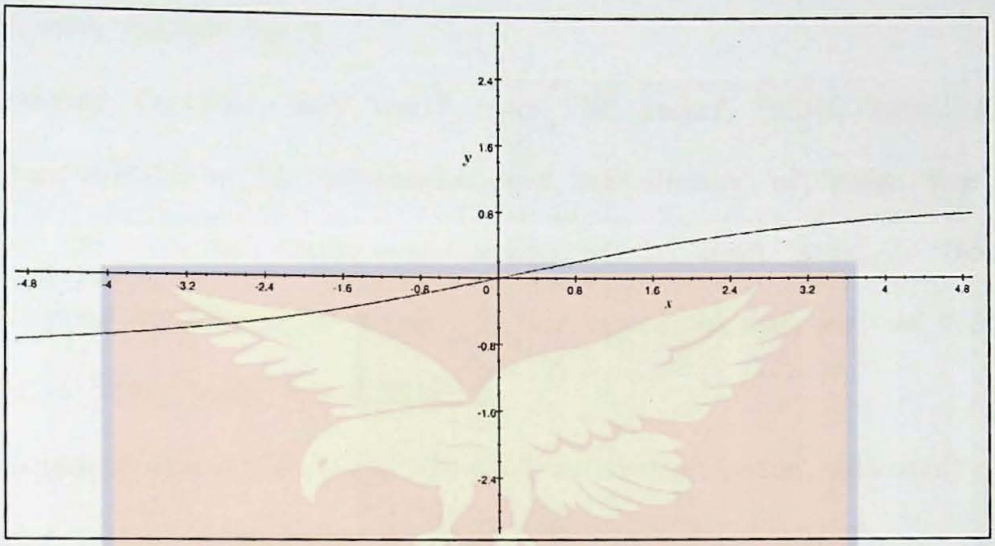

Figure 3: A graph of VADER's normalization

From the graph, it can be noted that a large x implies a large number of words to be evaluated. This will push the result closer to -1 or 1, and may not be a good representation of the actual sentiment score. In order to avoid the introduction of error and bias from large volumes of text, VADER works best on short pieces of text, making it ideal for analysis of tweets and sentences, as opposed to large documents like whole pages and more. One of the interesting features about VADER is that it is possible to see which words have been classified as positive, neutral or negative in a given piece of text. Let us consider the following sentences:

> *Prison systems the world over in recent times have a responsibility to ensure the reformation and rehabilitation of prisoners under their care as the era of mere warehousing of offenders is long gone. The unfortunate situation in Ghana's prison system in this regard is that our prisoners are fed at a paltry daily ration rate.*

VADER produces the following categorized word:

Positive: ['ensure', 'care']

Neutral: ['systems', 'the', 'world', 'over', 'in', 'recent', 'times', 'have', 'a', 'responsibility', 'to', 'the', 'reformation', 'and', 'rehabilitation', 'of', 'under', 'their', 'as', 'the', 'era', 'of', 'mere', 'warehousing', 'of', 'is', 'long', 'gone', '.', 'The', 'situation', 'in', 'Ghana', "'s", 'system', 'in', 'this', 'regard', 'is', 'that', 'our', 'are', 'fed', 'at', 'a', 'paltry', 'daily', 'ration', 'rate', '.']

Negative: ['Prison', 'prisoners', 'offenders', 'unfortunate', 'prison', 'prisoners']

Scores: {'neg': 0.269, 'neu': 0.647, 'pos': 0.083, 'compound': -0.9169}

The positive set of words show that *ensure* has a score of +1.6 and *care* has a score of +2.2, giving a total of +3.8.

The negative set of words show that *Prison* has a score of -2.3, *prisoners* has a score of -2.3, *offenders* has a score of -1.5, *unfortunate* has a score of -2.0, and *prison* and *prisoners* both have a score of -2.3.

The compound score, which is a normalised, weighted composite score, is the most important score in cases where a single measure of sentiment is required. It is calculated by applying the normalization in the following manner:

x is the sum of all the sentiment scores of the sentiment-laden words and α is normalised value of 15.

$$x = (1.6+2.2-2.3-2.3-1.5-2.0-2.3-2.3) = -8.9$$

so I have

$$\frac{-8.9}{\sqrt{(-8.9)^2 + 15}}$$

which gives us -0.9169, and is the normalised, weighted composite score.

The inbuilt nuances of VADER are expected to make it very well suited for short pieces of social media text like Twitter comments. Because of the limitation of the number of characters that a person can put up in a comment, social media tends to rely heavily on orthographic devices and punctuation in order to convey a deep emotion with as few words as possible.

3.9 Chapter Summary

These are the various tools and libraries that are used throughout the remainder of this report. Each chapter will have a detailed methodology for specific experiments that have been carried out, all of them using the outlined methods here as the foundation.

CHAPTER FOUR

RESULTS AND DISCUSSION

4.1 Introduction

The empirical studies presented in this section, examine how some sentiment analysis systems cope with modifiers. I also examine the extent to which modifiers in themselves may be sentiment-laden, and the subsequent effect those sentiments have on metaphors and oxymorons. I then examine whether or not it is beneficial for a SA system to detect the presence of metaphors in order to detect affect. To address these issues, the chapter has been organised into sections addressing three of the four main research questions, which are:

RQ1: To what extents do some current sentiment analysis systems cope with modifiers?

RQ2: What do modifiers contribute to two-word oxymorons?

RQ4: In order for a system to detect affect, is it beneficial for it to detect metaphor and oxymoron?

The third RQ, "What do modifiers contribute to affective metaphoric communication?" has been answered by a theoretical analysis outlined in Section 2.6 of chapter 2. Each section will also have an introduction to the empirical study undertaken for that sub section, with other sub-questions arising from the problem being discussed.

4.2 Sentiment Evaluation of Modifiers using WordNet and SentiWordNet

This section examines whether or not adverbs in themselves are sentiment-laden, and how WordNet (WN) and SentiWordNet (SWN) tie in definitions with sentiment scores, and whether or not WN and SWN have different scoring for adverbs that report sentiment and those that express sentiment.

For the purposes of the work done in this section, I will focus on adverbs of manner, which describe the way in which an action takes place, and usually answer the question of *how*. I will carry out a series of simple, manual inspections of a set of adverbs of manner, extract sentiment information using WN and SWN, and then compare some of their usage in sentences from the British National Corpus (BNC). This section will seek to address the following questions:

a) To what extent are adverbs in themselves sentiment-laden?

b) How do sentiment scores of adverbs in SWN reflect the definitions of corresponding synsets in WN?

c) Does SWN differentiate between adverbs of manner that are used to report sentiment and those that are used to express sentiment?

d) What are the implications of having a differing intuitive sentiment score from the computed SWN?

4.2.1 The Method of the Study

A total of 180 adverbs of manner were randomly gathered from books and Internet searches, and listed alphabetically in Microsoft Office Excel

(Appendix B). Out of the 180 adverbs gathered, I used the random function in Excel to randomly select 100 to be studied for the purposes of this experiment. Because the function selected a random 100 out of 180, repetitions did not occur. Each was checked for its senses in WN, and those senses had sentiment information extracted from SWN. Any adverb that had more than one sense was considered as many times as the sense since the sentiment scores differed (in most cases) from each other. For example, *extremely* has two adverbial senses, r.01 and r.02, and so I consider 'extremely' as two different adverbs. In total, there were 145 senses examined for the 100 adverbs, and these are outlined in Table 8. For each synset, I use the largest sentiment score to determine the final sentiment category. For example, the score set for the first adverbial sense of *rarely* is [0: 0.125: 0.875] in the format [positive: negative: neutral], and so it is classed as a neutral synset. The sentiment distribution of the various senses as extracted from SWN is listed in Table 9. In some cases, I have classified some adverbs as being both positive and negative because their positive score is equal to their negative score, and these are higher than the objective or neutral score. An example of this is the first adverbial sense of *frantically* with score [0.375: 0.375: 0.25] and the first adverbial sense of *madly* with scores [0.375: 0.375: 0.25]. In other cases, I have classified an adverb as both positive and neutral because the positive and neutral scores are equal, but greater than the neutral score. Examples include the first adverbial sense of *kindly,* which has a score set of [0.5: 0: 0.5], and the first adverbial sense of *warmly,* which has the score set [0.5: 0: 0.5], so the positive score (0.5) is equal to the neutral score (0.5) and they are greater than the negative score (0). Another set of adverbs has been classified as being both negative and neutral because the negative and neutral scores are equal and larger than the positive score. Examples of this include the first adverbial sense of *incredibly,* which has a score set of [0: 0.5: 0.5], and the third adverbial sense of *madly,* which has the score set [0: 0.5: 0.5].

Table 8: Adverbs of Manner and their Sentiment Scores

S/N	adverb	Sense	Positive Score	Negative Score	Neutral Score
1	absolutely	r.01	0.5	0	0.5
2	absolutely	r.02	0.5	0	0.5
3	accidentally	r.01	0.125	0	0.875
4	accidentally	r.02	0.125	0	0.875
5	accidentally	r.03	0.25	0.125	0.675
6	angrily	r.01	0	0.125	0.875
7	arguably	r.01	0	0	1
8	beautifully	r.01	0.375	0	0.625
9	brazenly	r.01	0.625	0	0.375
10	brightly	r.01	0.375	0.125	0.5
11	brilliantly	r.01	0.375	0.125	0.5
12	brilliantly	r.02	0.125	0.5	0.375
13	covetously	r.01	0.25	0	0.75
14	covetously	r.02	0.125	0	0.875
15	cunningly	r.01	0.375	0	0.625
16	cunningly	r.02	0.25	0	0.75
17	daringly	r.01	0.125	0	0.875
18	daringly	r.02	0.25	0	0.75
19	deceitfully	r.01	0.25		0.75
20	decidedly	r.01	0.25	0	0.75
21	deeply	r.01	0	0	1

22	deeply	r.02	0	0	1
23	destructively	r.01	0	0.125	0.875
24	devilishly	r.01	0	0.375	0.625
25	devilishly	r.02	0.125	0	0.875
26	devilishly	r.03	0	0.5	0.5
27	diabolically	r.01	0	0.375	0.625
28	disgracefully	r.01	0	0	1
29	easily	r.01	0.25	0	0.75
30	easily	r.02	0.125	0	0.875
31	easily	r.03	0.5	0	0.5
32	enormously	r.01	0	0.25	0.75
33	enthusiastically	r.01	0.375	0	0.625
34	enthusiastically	r.02	0.375	0	0.625
35	erroneously	r.01	0.25	0	0.75
36	eventually	r.01	0	0	1
37	explosively	r.01	0	0	1
38	explosively	r.02	0.125	0	0.875
39	extremely	r.01	0.625	0	0.375
40	extremely	r.02	0	0.125	0.875
41	fearfully	r.01	0	0	1
42	fearfully	r.02	0.25	0	0.75
43	fiendishly	r.01	0	0.375	0.625
44	flamboyantly	r.01	0.375	0	0.625
45	fondly	r.01	0.125	0	0.875
46	foolishly	r.01	0	0.625	0.375
47	frankly	r.01	0.375	0	0.625
48	frantically	r.01	0.375	0.375	0.25
49	generously	r.01	0.375	0	0.625
50	gently	r.01	0.125	0	0.875
51	gently	r.02	0.25	0	0.75
52	gently	r.03	0	0	1

53	graciously	r.01	0.375	0	0.625
54	greedily	r.01	0.125	0	0.875
55	happily	r.01	0.5	0.25	0.25
56	happily	r.02	0.375	0.25	0.375
57	harshly	r.01	0	0	1
58	harshly	r.02	0	0	1
59	hatefully	r.01	0.25	0	0.75
60	healthily	r.01	0.25	0	0.75
61	horribly	r.01	0	0.75	0.25
62	humbly	r.01	0.375	0	0.625
63	humbly	r.02	0.25	0	0.75
64	hurriedly	r.01	0	0	1
65	idiotically	r.01	0	0	1
66	impatiently	r.01	0.25	0	0.75
67	incredibly	r.01	0	0.5	0.5
68	incredibly	r.02	0.25	0	0.75
69	innocently	r.01	0	0	1
70	innocently	r.02	0.5	0	0.5
71	insolently	r.01	0.25	0	0.75
72	ironically	r.01	0	0.5	0.5
73	ironically	r.02	0.25	0	0.75
74	irritably	r.01	0.25	0	0.75
75	irritably	r.02	0	0.25	0.75
76	jealously	r.01	0	0	1
77	jealously	r.02	0.25	0	0.75
78	kindly	r.01	0.5	0	0.5
79	loudly	r.01	0	0	1
80	loudly	r.02	0	0	1
81	loudly	r.03	0	0	1
82	lovingly	r.01	0.125	0	0.875
83	madly	r.01	0.375	0.375	0.25

84	madly	r.02	0.5	0.25	0.25
85	madly	r.03	0	0.5	0.5
86	metaphorically	r.01	0.125	0	0.875
87	mysteriously	r.01	0.25	0	0.75
88	naughtily	r.01	0	0.5	0.5
89	neatly	r.01	0	0.125	0.875
90	negatively	r.01	0	0.75	0.25
91	negatively	r.02	0	0.375	0.625
92	noisily	r.01	0	0.125	0.875
93	obediently	r.01	0.375	0	0.625
94	obviously	r.01	0.5	0	0.5
95	patiently	r.01	0.125	0	0.875
96	peacefully	r.01	0.375	0	0.625
97	playfully	r.01	0.25	0	0.75
98	positively	r.01	0	0.25	0.75
99	positively	r.02	0.25	0	0.75
100	powerfully	r.01	0.125	0	0.875
101	powerfully	r.02	0	0	1
102	quickly	r.01	0	0	1
103	quickly	r.02	0	0	1
104	quickly	r.03	0	0	1
105	rarely	r.01	0	0.125	0.875
106	recklessly	r.01	0.25	0	0.75
107	regularly	r.01	0.125	0	0.875
108	regularly	r.02	0	0	1
109	regularly	r.03	0	0	1
110	reluctantly	r.01	0.25	0.25	0.5
111	repeatedly	r.01	0	0	1
112	restfully	r.01	0.25	0	0.75
113	rudely	r.01	0.25	0	0.75
114	sadly	r.01	0	0.625	0.375

115	sadly	r.02	0	0.25	0.725
116	sadly	r.03	0	0.875	0.125
117	safely	r.01	0.375	0	0.625
118	sarcastically	r.01	0.375	0	0.625
119	sensibly	r.01	0.375	0	0.625
120	seriously	r.01	0.25	0	0.75
121	seriously	r.02	0	0.25	0.75
122	shamefully	r.01	0	0	1
123	shockingly	r.01	0	0	1
124	shockingly	r.02	0	0	1
125	shrewdly	r.01	0.125	0	0.875
126	sleepily	r.01	0.25	0	0.75
127	slowly	r.01	0	0	1
128	slowly	r.02	0	0	1
129	sluggishly	r.01	0.25	0	0.75
130	stealthily	r.01	0.25	0	0.75
131	stupidly	r.01	0.25	0	0.75
132	successfully	r.01	0.125	0	0.875
133	suspiciously	r.01	0	0	1
134	tenderly	r.01	0.25	0	0.76
135	terminally	r.01	0	0	1
136	terribly	r.01	0.25	0	0.75
137	terribly	r.02	0	0.75	0.25
138	truthfully	r.01	0.125	0	0.875
139	understandably	r.01	0.125	0	0.875
140	wantonly	r.01	0.25	0	0.75
141	wantonly	r.02	0.125	0	0.875
142	warmly	r.01	0.5	0	0.5
143	warmly	r.02	0.25	0	0.75
144	wickedly	r.01	0	0.375	0.625
145	woefully	r.01	0	0.875	0.125

Table 9: Sentiment Distribution for Adverbial Senses

Sentiment	Number of Adverbs	Percentage
Positive	4	2.76%
Negative	8	5.52%
Neutral	118	81.38%
Positive and Negative	3	2.07%
Positive and Neutral	7	4.83%
Negative and Neutral	5	3.45%
Total	145	100%

4.2.2 The Results

I encountered a peculiar case with the adverb *shockingly*. WN gives three definitions with example sentences as follows:

- 1st Sense: Extremely: e.g., *Teachers were shockingly underpaid*
- 2nd Sense: Very badly: e.g., *They behaved shockingly at the funeral*
- 3rd Sense: So as to shock the feeling: e.g., *One day, she lost her temper, completely, suddenly and, even to herself, shockingly*; *Suddenly, shockingly, the clergyman's son was a desperado*

However, attempting to extract sentiment information for it from SWN threw an error that indicated that no third sense existed. This is because SWN does not provide a sentiment evaluation for the third sense of shockingly. The senses represented in SWN are the first (*Extremely*) and the second (*Very badly*), and both have been scored as perfectly neutral with a neutral score of 1. I therefore have only two senses for *shockingly* in the Table 8.

Even though all other senses of the listed words were found in SWN as outlined in WN, the 1% error still raises a question about the reliability of SWN when it comes to finding sentiment information on synsets that are in WN.

a) To what extents are adverbs themselves sentiment-laden?

From the definitions laid out in WordNet, there are a number of adverbs of manner that appear to be sentiment-laden. These adverbs would include (from our list in Table 8) negative-sentiment ones like *angrily, rudely, greedily, insolently, wickedly, fiendishly, stupidly, fearfully, recklessly, irritably, diabolically, devilishly, madly, harshly, wantonly, hatefully, deceitfully, disgracefully, sarcastically, shamefully, idiotically* and *destructively*. Another set of words that I would conclude as being positive-sentiment words would include *beautifully, innocently, restfully, neatly, graciously, warmly, truthfully, brightly, successfully, tenderly, kindly, fondly, lovingly* and *positively*. Computationally, however, SWN has rated all the above listed words as neutral. This will be examined in more detail in further research. SWN has shown that only 8.28% of our sample set has clearly either a positive or a negative sentiment; 10.35% have equal proportions of two different sentiments; and 81.38% are neutral.

b) How do sentiment scores of adverbs in SentiWordNet reflect the definitions of corresponding synsets in WordNet?

Even though 81.38% of the have been rated as neutral, some of them have meanings in WN that suggest that they are actually either positive or negative. Let us consider the following examples. According to WN, ***brilliantly*** has two adverbial senses. The first sense meaning "*with brightness*" and with an example sentence as "*the stars shone brilliantly*", and this was scored as neutral with the values [0.375: 0.125: 0.5]. This can be taken as reasonable since in essence, stars are expected to be shining brightly, and so its brightness would be stated more in a matter-of-fact way than in a way to express sentiment. The second sense means "*in an extremely intelligent way*" with an example sentence being *He solved the problem brilliantly*, and was scored by SentiWordNet as negative with the scores [0.125: 0.5: 0.375]. This cannot be correct, since *intelligence* is a positive attribute, and the presence of *extremely* further enhances that positive attribute.

I used the BNC to extract sentences[1] in which *brilliantly* had been used. There were 513 such instances, and so the random selection function in BNC was used to pick 50 sentences for manual inspection. These 50 sentences used the second WN sense. 25 of these sentences had the adverb placed before the word or phrase it was modifying (e.g. *William Perry has brilliantly charted the development of different perspectives amongst college students.*), and 25 had it appearing after the word it was modifying (e.g. *Pahdra Singh handled his on-air interview brilliantly.*). In the total set of 50 sentences, *brilliantly* was used in 34 sentences that intuitively had an overall positive sentential sentiment. It appeared in 14 sentences that had an overall neutral sentential sentiment, and 2 sentences that had an overall negative sentential sentiment. It was however observed that in all these sentences, the sentiment of the word *brilliantly* did not

[1] Examples of usage taken from the British National Corpus (BNC) were obtained under the terms of the BNC End User License. Copyright in the individual texts cited resides with the original IPR holders. For information and licensing conditions relating to the BNC, please see the web site at http://www.natcorp.ox.ac.uk/

become negative or neutral in itself. In the cases of the sentence that had a negative element like *The Samsung monitor and video card don't work brilliantly together* and *Then he responded brilliantly late on to parry a point-blank shot from the ill-starred Simpson*, the negativity of the sentences resulted from the negations *don't* in the first sentence and *late* in the second sentences. The word *brilliantly* itself remained positive. These are shown in Figure 4.

Another example is SWN's evaluation of the first sense of *fearfully* (Figure 5) as an absolute neutral with values [0: 0: 1], and which means *in fear* with *fear* being interpreted in WN as an *emotion experienced in anticipation of some specific pain or danger (usually accompanied by a desire to flee or fight)*. BNC lists *fearfully* in 31 sentences, which were all manually inspected. Again, picking a random set of 50 sentences, the distribution of usage is 0% positive, 12% neutral, and 88% negative, yet, SWN has rated it as absolutely neutral.

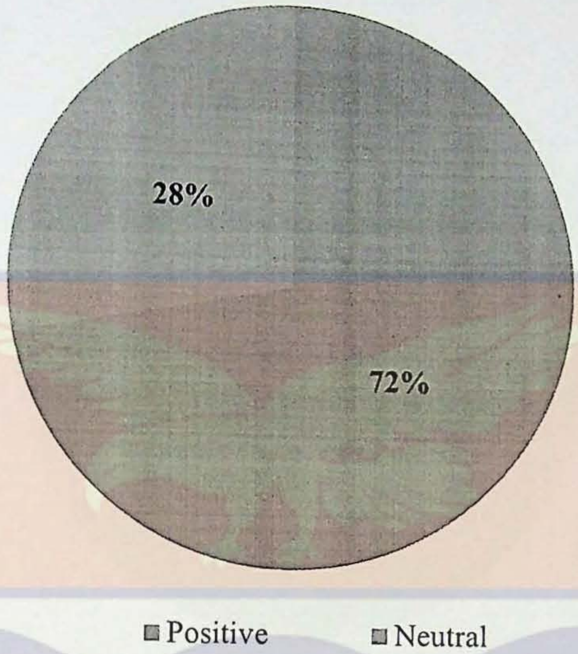

Figure 4: Usage of *brilliantly* in BNC

In another instance, SWN has evaluated *disgracefully* as a word with an absolutely neutral sentiment, and gives it the score set of [0: 0: 1]. This, again, calls into question the reliability of SWN, *disgracefully* has one adverbial sense in WordNet and it means *in a dishonourable manner or to a dishonourable degree*, with an example sentence being *His grades were disgracefully low.* BNC lists 24 instances of *disgracefully*, with one duplicate, and so 23 different sentences were manually inspected for context and intuitive sentiment. All 23 sentences had negative sentiment in the contexts in which they had been used, which raises a serious concern over how and why SWN would rate it as a neutral word.

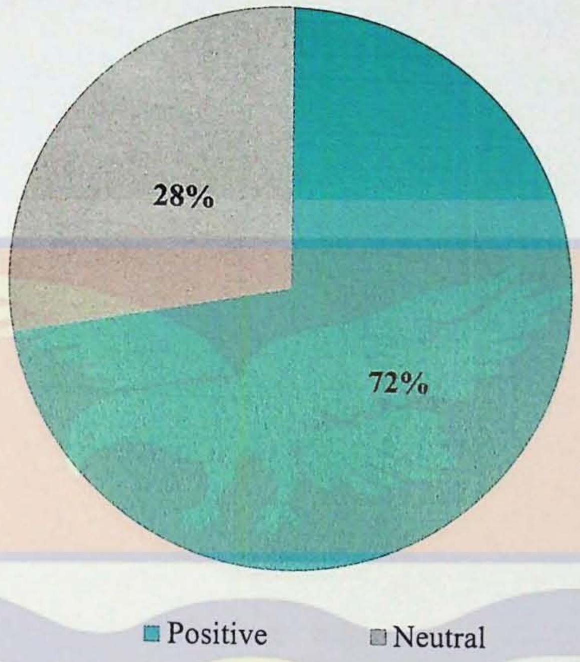

Figure 4: Usage of *brilliantly* in BNC

In another instance, SWN has evaluated *disgracefully* as a word with an absolutely neutral sentiment, and gives it the score set of [0: 0: 1]. This, again, calls into question the reliability of SWN, *disgracefully* has one adverbial sense in WordNet and it means *in a dishonourable manner or to a dishonourable degree*, with an example sentence being *His grades were disgracefully low.* BNC lists 24 instances of *disgracefully*, with one duplicate, and so 23 different sentences were manually inspected for context and intuitive sentiment. All 23 sentences had negative sentiment in the contexts in which they had been used, which raises a serious concern over how and why SWN would rate it as a neutral word.

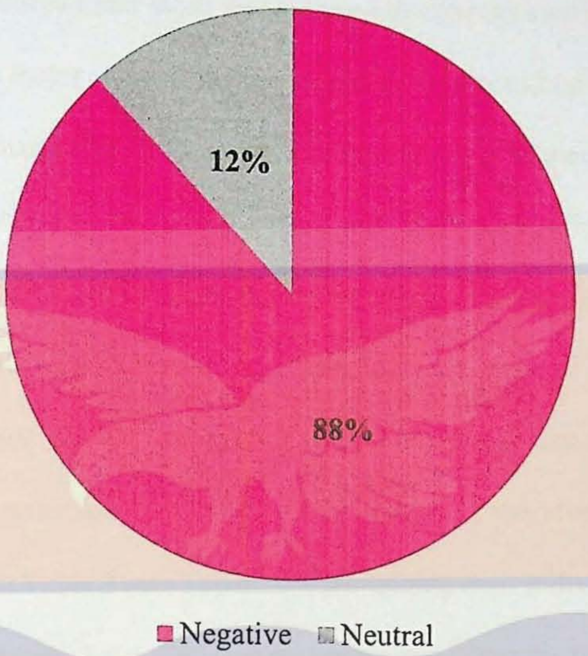

Figure 5: Usage of *fearfully* in BNC

Other synsets that have been rated 1 for perfect neutrality, but have definitions that suggest otherwise include the following:

- *shamefully.r.01 - in a dishonourable manner or to a dishonourable degree.*
    - Example: "*His grades were disgracefully low*"
- *idiotically.r.01 - in an idiotic manner.*
    - Example: "*What arouses the indignation of the honest satirist is not the fact that people in positions of power or influence behave idiotically.*"
- *foolishly.r.01 - without good sense or judgment.*
    - Example: *He acted foolishly when he agreed to come*
- *Destructively.r.01 - in a destructive manner.*
    - Example: "*He is destructively aggressive.*"

c) Does SentiWordNet differentiate between adverbs of manner that are used to report sentiment and those that are used to express sentiment?

There is a major issue of having sentiment that could be as a result of a writer ***reporting*** sentiment from a scenario, something or someone, and which reported sentiment may be devoid of the writer's own sentiment (e.g., *He angrily denied the accusation*), as against the sentiment being as a result of a writer ***expressing*** his sentiment about a scenario, something or someone (e.g., *Happily, he was not injured*). I noted in the previous section that SWN has rated some intuitively sentiment-laden adverbs as neutral. I therefore extracted all such adverbs from Table 8 into Table 10, maintaining their individual adverbial senses as some adverbs have different sentiment scores for the differing senses. For example, the 1st adverbial sense of *terribly* has a neutral meaning and use, while the 2nd sense has a negative meaning and usage. I therefore examined the meanings of all the extracted adverbs as laid out in WN, as well as the associated example sentences. There was a total of 57 adverbial senses for 49 adverbs of manner.

Table 10: Intuitively sentiment-laden adverbs of manner

SN	WORD	SENSE	SN	WORD	SENSE
1	angrily	r.01	30	madly	r.02
2	beautifully	r.01	31	naughtily	r.01
3	brazenly	r.01	32	negatively	r.01
4	brilliantly	r.02	33	negatively	r.02
5	covetously	r.01	34	noisily	r.01
6	covetously	r.02	35	obediently	r.01
7	cunningly	r.01	36	patiently	r.01
8	deceitfully	r.01	37	peacefully	r.01
9	destructively	r.01	38	positively	r.02
10	devilishly	r.01	39	recklessly	r.01
11	diabolically	r.01	40	reluctantly	r.01
12	disgracefully	r.01	41	rudely	r.01
13	erroneously	r.01	42	sadly	r.01
14	fearfully	r.01	43	sadly	r.02
15	fearfully	r.02	44	sadly	r.03
16	fiendishly	r.01	45	safely	r.01
17	foolishly	r.01	46	sarcastically	r.01
18	greedily	r.01	47	sensibly	r.01
19	happily	r.01	48	shamefully	r.01
20	happily	r.02	49	shockingly	r.02
21	harshly	r.01	50	shrewdly	r.01
22	harshly	r.02	51	stupidly	r.01
23	hatefully	r.01	52	successfully	r.01
24	horribly	r.01	53	terribly	r.02
25	idiotically	r.01	54	wantonly	r.01
26	insolently	r.01	55	wantonly	r.02
27	irritably	r.01	56	wickedly	r.01
28	jealously	r.02	57	woefully	r.01
29	lovingly	r.01			

Using the laid out WN definitions and the example sentences, these adverbial senses were split into different categories. Table 11 lists adverbs that ***report*** negative sentiment, Table 12 lists adverbs that ***express*** negative sentiment, Table 13 lists adverbs that ***report*** positive sentiment, and Table 14 lists adverbs that ***express*** positive sentiment.

Table 11: Adverbial Senses that Report Negative Sentiment

REPORTING NEGATIVE SENTIMENT					
S/N	adverb	Sense	Pos	Neg	Neu
1	angrily	r.01	0	0.125	0.875
2	brazenly	r.01	0.625	0	0.375
3	covetously	r.01	0.25	0	0.75
4	covetously	r.02	0.125	0	0.875
5	destructively	r.01	0	0.125	0.875
6	devilishly	r.01	0	0.375	0.625
7	diabolically	r.01	0	0.375	0.625
8	erroneously	r.01	0.25	0	0.75
9	fearfully	r.01	0	0	1
10	fearfully	r.02	0.25	0	0.75
11	fiendishly	r.01	0	0.375	0.625
12	greedily	r.01	0.125	0	0.875
13	harshly	r.01	0	0	1
14	hatefully	r.01	0.25	0	0.75
15	idiotically	r.01	0	0	1
16	insolently	r.01	0.25	0	0.75
17	irritably	r.01	0.25	0	0.75
18	jealously	r.02	0.25	0	0.75
19	madly	r.02	0.5	0.25	0.25
20	naughtily	r.01	0	0.5	0.5
21	negatively	r.01	0	0.75	0.25

22	negatively	r.02	0	0.375	0.625
23	noisily	r.01	0	0.125	0.875
24	reluctantly	r.01	0.25	0.25	0.5
25	sadly	r.02	0	0.25	0.725
26	sadly	r.03	0	0.875	0.125
27	wantonly	r.02	0.125	0	0.875
28	wickedly	r.01	0	0.375	0.625

Table 12: Adverbial Senses that Express Negative Sentiment

EXPRESSING NEGATIVE SENTIMENT					
S/N	adverb	Sense	Pos	Neg	Neu
1	deceitfully	r.01	0.25	0	0.75
2	disgracefully	r.01	0	0	1
3	foolishly	r.01	0	0.625	0.375
4	harshly	r.02	0	0	1
5	horribly	r.01	0	0.75	0.25
6	recklessly	r.01	0.25	0	0.75
7	rudely	r.01	0.25	0	0.75
8	sadly	r.01	0	0.625	0.375
9	sarcastically	r.01	0.375	0	0.625
10	shamefully	r.01	0	0	1
11	shockingly	r.02	0	0	1
12	stupidly	r.01	0.25	0	0.75
13	terribly	r.02	0	0.75	0.25
14	wantonly	r.01	0.25	0	0.75
15	woefully	r.01	0	0.875	0.125

Table 13: Adverbial sense that report positive sentiment

POSITIVE					
S/N	adverb	Sense	Pos	Neg	Neu
1	brilliantly	r.02	0.125	0.5	0.375
2	cunningly	r.01	0.375	0	0.625
3	happily	r.01	0.5	0.25	0.25
4	lovingly	r.01	0.125	0	0.875
5	obediently	r.01	0.375	0	0.625
6	patiently	r.01	0.125	0	0.875
7	peacefully	r.01	0.375	0	0.625
8	positively	r.02	0.25	0	0.75
9	shrewdly	r.01	0.125	0	0.875
10	successfully	r.01	0.125	0	0.875

Table 14: Adverbial Senses that Express Positive Sentiment

POSITIVE					
S/N	adverb	Sense	Pos	Neg	Neu
1	beautifully	r.01	0.375	0	0.625
2	happily	r.02	0.375	0.25	0.375
3	safely	r.01	0.375	0	0.625
4	sensibly	r.01	0.375	0	0.625

There doesn't appear to be any clear pattern as to how SWN evaluates the various *reporting* and *expressing* cases, and may well be the reason why there is a disparity between the meanings of the words as laid out in WN, and the sentiment attached to them as laid out in SWN. A full table of the meanings and example sentences are presented in Appendix A. Further research will be undertaken to establish a clear pattern between the *expressing* and the *reporting* sense. Some adverbs were noted to have one sense being used in the reporting context, and another being used in the expressing sentence, an example being *harshly*, where the first sense *reports* and the second sense expresses. In this case, both contexts have been rated as absolute neutral with an objective score of 1, which is in contrast to the definitions for both senses, sense 1 meaning "in a harsh or unkind manner" with an example sentence "That's enough!' he cut in harshly", and sense 2 meaning "in a harsh and grating manner" with an example sentence "her voice fell gratingly on our ears". Another example is *fearfully* which has both senses being rated as neutral with the first having an objective or neutral score of 0.75 and a positive score of 0.25, while the second sense has an absolute neutral score of 1. The first sense has been used in an expression sense ("They were fearfully attacked") and the second in a reporting sense ("she hurried down the stairs fearfully").

d) What are the implications of having a differing intuitive sentiment score from the computed SentiWordNet score?

Initiators of discourse may use an adverb in their communication with the intent of putting across a certain degree of sentiment for a specific purpose, but, if the message is being interpreted by a sentiment analysis system that is based on SWN only without adjustments and modifications to incorporate the lapses I have pointed out, the final score may be deceptive, in which case, meaning will be lost, and decisions based on that computed meaning will introduce errors into discourse.

4.2.3 Summary

In summary, it is the case that some of the synsets in the SentiWordNet lexical resource are incorrectly labelled with sentiment categorisation, and so may introduce logical errors in computations that rely solely on the sentiment scores extracted from it. This could be as a result of the lack of distinction between the reporting and the expressing ways of using the adverbs. Further research will be required to establish this hypothesis. It has also been confirmed that some adverbs of manner do in themselves contain sentiment, which serves to further enhance the overall sentiment of words or phrases that they modify. This said, I will still use SWN for subsequent studies in later sections of this chapter, and I will attempt to partly offset the wrong sentiment labels with manual inspections and independent sentiment labels.

4.3 The Contribution of Modifiers to Two-Word Oxymorons

This section continues the discussions from the previous section by extending the analyses of the use of adverbs in general and adverbs of manner specifically, to modifiers in the occurrence of oxymorons, and how affect can be computed from them within a sentence.

4.3.1 The Method of the Study

In the light of modifiers and their effect in discourse, I will seek to answer the following questions in this section about two-word oxymorons that have the modifier occurring just before the word it modifies:

a) Is the meaning of a sentence altered when the modifier in the oxymoron is removed?

b) Do the modifiers in two-word oxymorons have inherent sentiment values?

c) What is the significance of the polarity of the modifier in a two-word oxymoron?

d) If oxymorons are isolated, do they present the same affect as when used in sentences? (Does context matter?)

A total of 233 two-word oxymorons were gathered from books and Internet searches, and listed alphabetically in Microsoft Office Excel (Appendix C). The random function from Excel was used to randomly select 50 of those oxymorons, and manually inspecting them to ensure that repetitions did not occur. The different senses of these word-pairs were analysed in order to ensure that both words are being used in the same sphere of meaning. For example, the first adjectival sense of the word *beautiful* means *delighting the senses or exciting intellectual or emotional admiration*, and which by extension gives us *beautifully*, which also means *in a beautiful manner*. *Ugly* which is an antonym for *beautiful*, has its first adjectival sense being *displeasing to the senses*, and so both *beautifully* and *ugly* are in the same sphere of acting on the senses. The complete list of words (Word 1: W1), and their antonym pairs (Word 2: W2) is presented in Table 15. As an added check for contrast, all the chosen sense-pairs were compared using the Wu-Palmer similarity function in python, which is a method that is used to score words based on how alike the senses of two words are, and where their synsets occur in relation to each other in the hypernym tree using the shortest path distance between them as one of the main metrics in calculation.

Table 15: Words, Senses, Antonym Pairs and Resulting Oxymorons

S/N	WORD 1 (W1)	SENSE (S1)	WORD 2 (W2)	SENSE (S2)	OXYMORON (O)
1	Advantageous	a.01	Disadvantage	n.01	Advantageous disadvantage
2	Alone	a.01	Together	r.03	Alone together
3	Beautifully	r.01	Ugly	a.01	Beautifully ugly
4	Bitter	a.06	Sweet	a.01	Bitter sweet
5	Blind	a.01	Sight	n.03	Blind sight
6	Clever	a.03	Foolishness	n.02	Clever foolishness
7	Constant	n.01	Variable	n.01	Constant variable
8	Cruel	a.01	Kindness	n.01	Cruel kindness
9	Dark	a.01	Light	n.09	Dark light
10	Deafening	a.01	Silence	n.02	Deafening silence
11	Deeply	r.02	Superficial	a.02	Deeply superficial
12	Definitely	r.01	Maybe	r.01	Definitely maybe
13	Faithfully	n.02	Unfaithful	a.04	Faithfully unfaithful
14	Falsely	r.02	True	a.01	Falsely true
15	Farewell	n.02	Reception	n.02	Farewell reception
16	Fine	a.01	Mess	n.01	Fine mess
17	Free	a.01	Prisoner	n.01	Free prisoner

18	Friendly	a.02	Hostility	n.01	Friendly hostility
19	Genuine	a.01	Imitation	n.02	Genuine imitation
20	Honest	a.05	Lie	n.01	Honest lie
21	Living	a.01	Dead	a.01	Living dead
22	Love	n.01	Hate	n.01	Love hate
23	Minor	a.01	Crisis	n.02	Minor crisis
24	New	a.01	Antique	a.02	New antique
25	Objective	a.03	Opinion	n.01	Objective opinion
26	Old	a.02	News	n.01	Old news
27	Only	a.01	Choice	n.02	Only Choice
28	Openly	r.01	Closed	a.09	Openly closed
29	Ordered	a.01	Disorder	n.02	Ordered disorder
30	Ordered	a.01	Chaos	n.01	Ordered chaos
31	Original	a.04	Copy	n.02	Original copy
32	Passive	a.01	Aggressive	a.01	Passive aggressive
33	Peaceful	a.01	War	n.01	Peaceful war
34	Positively	r.02	Negative	a.01	Positively negative
35	Public	a.01	Secret	n.01	Public secret
36	Random	a.01	Order	n.05	Random order
37	Restrictive	a.01	Freedom	n.01	Restrictive freedom
38	Same	a.01	Difference	n.01	Same difference
39	Seriously	r.01	Funny	n.01	Seriously funny
40	Silent	a.01	Scream	n.01	Silent scream

41	Simple	a.01	Complication	n.02	Simple complication
42	Small	a.01	Crowd	n.01	Small crowd
43	Sophisticated	a.01	Naïveté	n.01	Sophisticated naïveté
44	Strangely	r.01	Familiar	a.01	Strangely familiar
45	Sweet		Sorrow		Sweet sorrow
46	Theoretical	a.01	Experience	n.01	Theoretical experience
47	Tragic	a.01	Comedy	n.01	Tragic comedy
48	True	a.01	Myth	n.01	True myth
49	Unpopular	a.01	Celebrity	n.02	Unpopular celebrity
50	Working	a.01	Holiday	n.01	Working holiday

The sentences in which these two-word oxymorons were used (as found in the searches for the selected set of 50 oxymorons) were also listed. This is presented in Table 16.

4.3.2 The results

a) Is the meaning of a sentence altered when the modifier in the oxymoron is removed?

In order to examine the effects of removing the modifiers, I generated auxiliary sentences by re-writing the original sentences without the modifiers, and this is presented in Table 16.

Table 16: Oxymoronic Sentences and their Auxiliary Sentences

S/N	OXYMORON	SENTENCE	AUXILIARY SENTENCE
1	Advantageous disadvantage	Being female can be an advantageous disadvantage in some specialized fields.	Being female can be a disadvantage in some specialized fields.
2	Alone together	They couldn't wait to get away alone together	They couldn't wait to get away together
3	Beautifully ugly	That Persian rug is beautifully ugly.	That Persian rug is ugly.
4	Bitter sweet	A wave of bitter sweet memories washed over her.	A wave of sweet memories washed over her.
5	Blind sight	A lethargic demeanour is an easy way to blind sight the unethical and illegal act of bribery.	A lethargic demeanour is an easy way to sight the unethical and illegal act of bribery.
6	Clever foolishness	An oxymoron is simply clever foolishness	An oxymoron is simply foolishness
7	Constant variable	The value of a constant variable does not change	The value of a variable does not change
8	Cruel kindness	Forcing your child to wake up early in order to attend school may be seen by some as an act of cruel kindness.	Forcing your child to wake up early in order to attend school may be seen by some as an act of kindness.
9	Dark light	There is an eerie dark light around him.	There is an eerie light around him.

10	Deafening silence	After her verbal tirade, the room filled with a deafening silence	After her verbal tirade, the room filled with silence
11	Deeply superficial	Akosua has deeply superficial moral values	Akosua has superficial moral values
12	Definitely maybe	I will definitely maybe travel the world when I go on retirement.	I will maybe travel the world when I go on retirement.
13	Faithfully unfaithful	Being faithfully unfaithful kept him falsely true	Being unfaithful kept him falsely true
14	Falsely true	His honour rooted in dishonour, and faith unfaithful kept him falsely true	His honour rooted in dishonour, and faith unfaithful kept him true
15	Farewell reception	She had recently been invited to a farewell reception.	She had recently been invited to a reception.
16	Fine mess	She left a fine mess in the room	She left a mess in the room
17	Free prisoner	Serving as a house help is akin to being a free prisoner.	Serving as a house help is akin to being a prisoner.
18	Friendly hostility	He appeared to be joking even though he cut her to size by his remarks - a clear case of friendly hostility.	He appeared to be joking even though he cut her to size by his remarks - a clear case of hostility.
19	Genuine imitation	This is a genuine imitation iPhone X	This is an imitation iPhone X

20	Honest lie	The politician was caught up in an honest lie.	The politician was caught up in a lie.
21	Living dead	His dirge was enough to let the living dead walk.	His dirge was enough to let the dead walk.
22	Love hate	Theirs is a real love hate relationship	Theirs is a real hate relationship
23	Minor crisis	He couldn't help her because he was involved in his own minor crisis	He couldn't help her because he was involved in his own crisis
24	new antique	I just acquired a new antique	I just acquired an antique
25	Objective opinion	I wish I could get his objective opinion	I wish I could get his opinion
26	Old news	The story is old news	The story is news
27	Only Choice	It looks like taking the bus is your only choice.	It looks like taking the bus is your choice.
28	Openly closed	The exhibition was openly closed to the public.	The exhibition was closed to the public.
29	Ordered chaos	Her closet is a true depiction of ordered chaos.	Her closet is a true depiction of chaos.
30	Ordered disorder	The room was put into an ordered disorder to create a natural effect.	The room was put into a disorder to create a natural effect.
31	Original copy	You are required to submit original copies of your documents to the embassy	You are required to submit copies of your documents to the embassy

32	Passive aggressive	Kwabena has a passive aggressive personality	Kwabena has an aggressive personality
33	Peaceful war	Is there such a thing as a peaceful war?	Is there such a thing as a war?
34	Positively negative	It is positively negative to hammer on only the faults of others.	It is negative to hammer on only the faults of others.
35	Public secret	The family's past is a public secret	The family's past is a secret
36	Random order	The codes for the buttons were generated in a random order.	The codes for the buttons were generated in an order.
37	Restrictive freedom	Being under house arrest is the same as living a life of restrictive freedom	Being under house arrest is the same as living a life of freedom
38	Same difference	Sending Joyce or Gifty is the same difference in my opinion.	Sending Joyce or Gifty is a difference in my opinion.
39	Seriously funny	That Nigerian movie is seriously funny	That Nigerian movie is funny
40	Silent scream	Didi's mouth opened in a silent scream	Didi's mouth opened in a scream
41	Simple complication	Having a baby as a teenager is a simple complication to one's future.	Having a baby as a teenager is a complication to one's future.
42	Small crowd	A small crowd had gathered at the scene of the accident	A crowd had gathered at the scene of the accident

43	Sophisticated naïveté	Sophie has an air of sophisticated naiveté about her.	Sophie has an air of naiveté about her.
44	Strangely familiar	The flight attendant looks strangely familiar	The flight attendant looks familiar
45	Sweet sorrow	Parting is such sweet sorrow	Parting is such sorrow
46	Theoretical experience	It is recommended that you put your theoretical experience into practice in order to make headway in your field of expertise.	It is recommended that you put your experience into practice in order to make headway in your field of expertise.
47	Tragic comedy	We laughed through the tragic comedy	We laughed through the comedy
48	True myth	The movie Is based on a true myth	The movie Is based on a myth
49	Unpopular celebrity	Audrey has managed to become an unpopular celebrity	Audrey has managed to become a celebrity
50	Working holiday	My trip to the Caribbean was very much a working holiday	My trip to the Caribbean was very much a holiday

With the removal of the modifier, I had a moderate to significant change in 50% of the sentences. These are presented in Table 17. One such significant case is that of the sentence with the oxymoron *working holiday*. The point of the original sentence, *My trip to the Caribbean was very much a working holiday,* is that he **worked** on his trip, while the auxiliary statement points to the fact that he had an actual holiday. Another case is the sentence *The family's past is a public secret*. Anything that is public secret suggests that its common knowledge. However, the auxiliary statement, *The family's past is secret,* implies that their past is unknown. Another such example is, *Theirs is a real love hate relationship* (which could be a case that they get on very well sometimes and clash very badly at other times) and the auxiliary, *Theirs is a real hate relationship* (which is a case that they don't get on well at all).

There was one peculiar case where the meaning was not quite correct after the modifier was removed, as in the case of *constant variable*. It is semantically correct to say that *The value of a constant variable does not change*, but semantically incorrect to say that *The value of a variable does not change*, as the very meaning of *variable* means that it is subject to change.

Table 17: Auxiliary Sentences that have Significant Change in Meaning with the Removal of the Modifiers

S/N	OXYMORON	SENTENCE	AUXILIARY SENTENCE
1	Advantageous disadvantage	Being female can be an advantageous disadvantage in some specialized fields.	Being female can be a disadvantage in some specialized fields.
2	Alone together	They couldn't wait to get away alone together	They couldn't wait to get away together
3	Blind sight	A lethargic demeanour is an easy way to blind sight the unethical and illegal act of bribery.	A lethargic demeanour is an easy way to sight the unethical and illegal act of bribery.

4	Clever foolishness	An oxymoron is simply clever foolishness	An oxymoron is simply foolishness
5	Constant variable	The value of a constant variable does not change	The value of a variable does not change
6	Falsely true	His honour rooted in dishonour, and faith unfaithful kept him falsely true	His honour rooted in dishonour, and faith unfaithful kept him true
7	Genuine imitation	This is a genuine imitation iPhone X	This is an imitation iPhone X
8	Honest lie	The politician was caught up in an honest lie.	The politician was caught up in a lie.
9	Love hate	Theirs is a real love hate relationship	Theirs is a real hate relationship
10	Objective opinion	I wish I could get his objective opinion	I wish I could get his opinion
11	Old news	The story is old news	The story is news
12	Only Choice	It looks like taking the bus is your only choice.	It looks like taking the bus is your choice.
13	Ordered disorder	The room was put into an ordered disorder to create a natural effect.	The room was put into a disorder to create a natural effect.
14	Original copy	You are required to submit original copies of your documents to the embassy	You are required to submit copies of your documents to the embassy
15	Positively negative	It is positively negative to hammer on only the faults of others.	It is negative to hammer on only the faults of others.

16	Public secret	The family's past is a public secret	The family's past is a secret
17	Restrictive freedom	Being under house arrest is the same as living a life of restrictive freedom	Being under house arrest is the same as living a life of freedom
18	Same difference	Sending Joyce or Gifty is the same difference in my opinion.	Sending Joyce or Gifty is a difference in my opinion.
19	Silent scream	Didi's mouth opened in a silent scream	Didi's mouth opened in a scream
20	Sophisticated naïveté	Sophie has an air of sophisticated naiveté about her.	Sophie has an air of naiveté about her.
21	Theoretical experience	It is recommended that you put your theoretical experience into practice in order to make headway in your field of expertise.	It is recommended that you put your experience into practice in order to make headway in your field of expertise.
22	Tragic comedy	We laughed through the tragic comedy	We laughed through the comedy
23	True myth	The movie Is based on a true myth	The movie Is based on a myth
24	Unpopular celebrity	Audrey has managed to become an unpopular celebrity	Audrey has managed to become a celebrity
25	Working holiday	My trip to the Caribbean was very much a working holiday	My trip to the Caribbean was very much a holiday

b. Do modifiers in two-word oxymorons have inherent sentiment values?

In the case of our two-word oxymorons, the first words were syntactically the modifiers. Each of these words had their component sentiment values extracted in a format [pos: neg: neu] to show the positive, negative and neutral scores as stored in SentiWordNet 3.0. These are listed in Table 18.

Table 18: Sentiment Values of Qualifying Words in the Oxymorons

S/N	MODIFIER	SENSE	SENT_VAL [pos:neg:neu]
1	Advantageous	a.01	[0.625: 0: 0.375]
2	Alone	a.01	[0: 0: 1]
3	Beautifully	r.01	[0.375: 0: 0.625]
4	Bitter	a.06	[0: 0.375: 0.625]
5	Blind	a.01	[0: 0: 1]
6	Clever	a.03	[0.625: 0: 0.375]
7	Constant	n.01	[0: 0.25: 0.75]
8	Cruel	a.01	[0: 0.625: 0.375]
9	Dark	a.01	[0.125: 0.125: 0.75]
10	Deafening	a.01	[0.125: 0: 0.875]
11	Deeply	r.02	[0: 0: 1]
12	Definitely	r.01	[0.25: 0: 0.75]
13	Faithfully	r.01	[0.25: 0: 0.75]
14	Falsely	r.02	[0.25: 0: 0.75]
15	Farewell	n.02	[0: 0: 1]
16	Fine	a.01	[0.375: 0: 0.625]
17	Free	a.01	[0.375: 0: 0.625]
18	Friendly	a.02	[0.625: 0.25: 0.125]
19	Genuine	a.01	[0.364: 0.636: 0]
20	Honest	a.05	[0.75: 0: 0.25]
21	Living	a.01	[0: 0.125: 0.875]

22	Love	n.01	[0.625: 0: 0.375]
23	Minor	a.01	[0.25: 0.625: 0.125]
24	New	a.01	[0.375: 0: 0.625]
25	Objective	a.03	[0.375: 0.375: 0.25]
26	Old	a.02	[0: 0.375: 0.625]
27	Only	a.01	[0: 0: 1]
28	Openly	r.01	[0.125: 0: 0.875]
29	Ordered	a.01	[0: 0: 1]
30	Ordered	a.01	[0: 0: 1]
31	Original	a.04	[0: 0.25: 0.75]
32	Passive	a.01	[0.375: 0.25: 0.375]
33	Peaceful	a.01	[0.25: 0: 0.75]
34	Positively	r.02	[0.25: 0: 0.75]
35	Public	a.01	[0: 0.125: 0.875]
36	Random	a.01	[0.125: 0: 0.875]
37	Restrictive	a.01	[0: 0: 1]
38	Same	a.01	[0: 0: 1]
39	Seriously	r.01	[0.25: 0: 0.75]
40	Silent	a.01	[0.125: 0.375: 0.5]
41	Simple	a.01	[0.125: 0.375: 0.5]
42	Small	a.01	[0: 0.375: 0.625]
43	Sophisticated	a.01	[0.625: 0: 0.375]
44	Strangely	r.01	[0.25: 0: 0.75]
45	Sweet	a.04	[0.875: 0: 0.125]
46	Theoretical	a.01	[0: 0: 1]
47	Tragic	a.01	[0: 0.625: 0.375]
48	True	a.01	[0.5: 0.375: 0.125]
49	Unpopular	a.01	[0.125: 0.125: 0.75]
50	Working	a.01	[0.125: 0: 0.875]

It was concluded from the results that the modifiers do have inherent sentiment value since they are essentially like any other words, though a large number of them appeared to be completely or largely neutral. This is shown in Table 19 and Figure 6. There were no modifiers that were totally positive or totally negative. They were grouped into the following categories:

- Totally neutral – if the neutral value is 1 with zero positivity and zero negativity (neutral value = 1)
- Largely neutral – if the neutral score is greater than or equal to 0.5, but less than 1 (1 > neutral score ≥ 0.5)
- Largely positive – if the positivity score is greater than or equal to +0.5, but less than 1 (1>positive value ≥ 0.5)
- Largely negative – if the negativity score is greater than or equal to -0.5, but less than -1 (-1 > negative score ≥ -0.5)
- Positive and negative – if the positivity and negativity scores are the same, and that score is greater than the neutral score ((positive score = negative score) > neutral score))
- Positive and neutral – if the positivity and neutral scores are the same, and that score is greater than the negative score. ((positive score = neutral score) > negative score)

Table 19: Sentiment Distribution of Modifiers

S/N	CATEGORY	NUMBER OF WORDS	TOTAL
1	Totally neutral	11	22%
2	Largely neutral	25	50%
3	Largely positive	8	16%
4	Largely negative	4	8%
5	Positive and negative	1	2%
6	Positive and neutral	1	2%
	Total	50	100%

Comparing to table 9 which outlined the sentiment distribution for adverbial senses, SWN scored, in the order of adverbs of manner against modifiers, 81.38% vs 72% neutral, 5.52% vs 8% negative, 2.76% vs 16% positive, and 10.35% vs 4% mixed sentiments. SWN appears to score a large number of adverbs/modifiers as neutral, which, to some extent, suggest that the identified disparity between meanings of words and the sentiment scores are relevant.

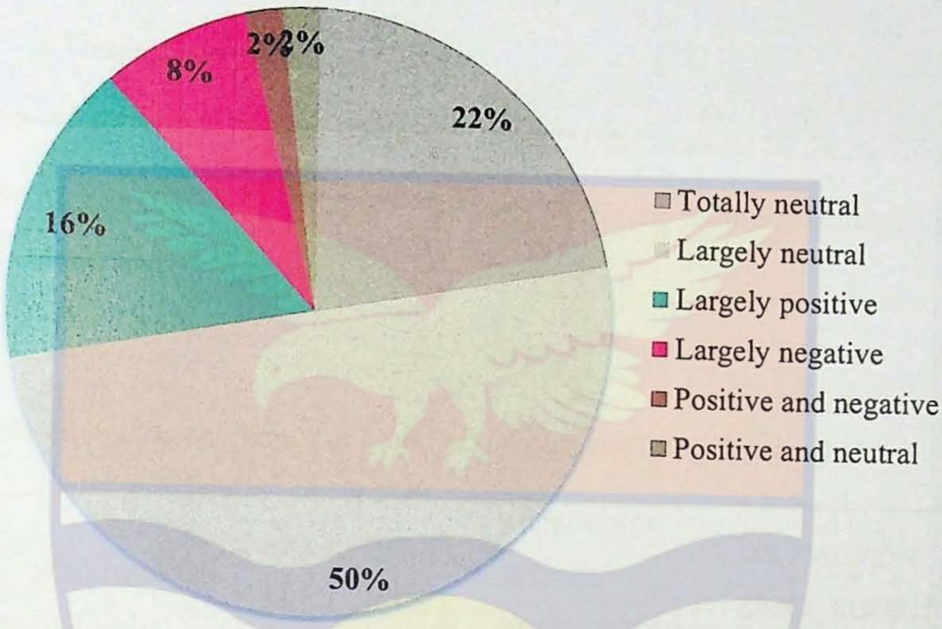

Figure 6: Sentiment Distribution of Modifiers

c). What is the significance of the polarity of the modifier in a two-word oxymoron?

Each two-word oxymoron was split into the separate words and their constituent sentiment scores obtained from SWN, ignoring the suspected inherent errors of SWN. These are shown in Table 20. To obtain the scores for the oxymoron as a unit, the score set in the format [pos: neg: neu] constituting the positive score (***pos***), negative score ***neg*** and the neutral score ***neu*** was obtained for both the modifier (**q**) and the modified word (**w**), and the simple mean calculated to obtain the score set for the oxymoron (O) as O[pos: neg: neu].

For example, for the oxymoron

Deafening silence

the score set for the modifier is **q** [0.125: 0: 0.875], the score set for the modified word is **w** [0.125: 0.375: 0.5], and the score set for the resulting oxymoron is **O**[0.125: 0.1875: 0.6875].

Table 20: Sentiment Scores of Modifiers, Words and Resulting Oxymorons

	OXYMORON	MODIFIER SENT_SCORE	MODIFIED WORD SENT_SCORE	OXYMORON SENT_SCORE
1	Advantageous disadvantage	[0.625: 0: 0.375]	[0: 0.75: 0.25]	[0.3125: 0.375: 0.3125]
2	Alone together	[0: 0: 1]	[0: 0: 1]	[0: 0: 1]
3	Beautifully ugly	[0.375: 0: 0.625]	[0: 0.375: 0.625]	[0.1875: 0.1875: 0.625]
4	Bitter sweet	[0: 0.375: 0.625]	[0: 0: 1]	[0: 0.1875: 0.8125]
5	Blind sight	[0: 0: 1]	[0: 0: 1]	[0: 0: 1]
6	Clever foolishness	[0.625: 0: 0.375]	[0.375: 0.375: 0.25]	[0.5: 0.1875: 0.3125]
7	Constant variable	[0: 0.25: 0.75]	[0: 0: 1]	[0: 0.125: 0.875]
8	Cruel kindness	[0: 0.625: 0.375]	[0.625: 0.375: 0]	[0.3125: 0.5: 0.1875]

9	Dark light	[0.125: 0.125: 0.75]	[0: 0.125: 0.875]	[0.0625: 0.125: 0.8125]
10	Deafening silence	[0.125: 0: 0.875]	[0.125: 0.375: 0.5]	[0.125: 0.1875: 0.6875]
11	Deeply superficial	[0: 0: 1]	[0: 0: 1]	[0: 0: 1]
12	Definitely maybe	[0.25: 0: 0.75]	[0: 0: 1]	[0.125: 0: 0.875]
13	Faithfully unfaithful	[0.25: 0: 0.75]	[0: 0.5: 0.5]	[0.125: 0.25: 0.625]
14	Falsely true	[0.25: 0: 0.75]	[0.5: 0.375: 0.125]	[0.375: 0.1875: 0.4375]
15	Farewell reception	[0: 0: 1]	[0.5: 0: 0.5]	[0.25: 0: 0.75]
16	Fine mess	[0.375: 0: 0.625]	[0: 0.125: 0.875]	[0.1875: 0.0625: 0.75]
17	Free prisoner	[0.375: 0: 0.625]	[0: 0: 1]	[0.1875: 0: 0.8125]
18	Friendly hostility	[0.625: 0.25: 0.125]	[0.125: 0.75: 0.125]	[0.375: 0.5: 0.125]
19	Genuine imitation	[0.364: 0.636: 0]	[0: 0: 1]	[0.182: 0.318: 0.5]
20	Honest lie	[0.75: 0: 0.25]	[0: 0: 1]	[0.375: 0: 0.625]
21	Living dead	[0: 0.125: 0.875]	[0: 0.75: 0.25]	[0: 0.4375: 0.5625]
22	Love hate	[0.625: 0: 0.375]	[0.125: 0.375: 0.5]	[0.375: 0.1875: 0.4375]
23	Minor crisis	[0.25: 0.625: 0.125]	[0: 0: 1]	[0.125: 0.3125: 0.5625]

24	New antique	[0.375: 0: 0.625]	[0: 0: 1]	[0.1875: 0: 0.8125]
25	Objective opinion	[0.375: 0.375: 0.25]	[0: 0.625: 0.375]	[0.1875: 0.5: 0.3125]
26	Old news	[0: 0.375: 0.625]	[0: 0: 1]	[0: 0.1875: 0.8125]
27	Only choice	[0: 0: 1]	[0: 0: 1]	[0: 0: 1]
28	Openly closed	[0.125: 0: 0.875]	[0: 0: 1]	[0.0625: 0: 0.9375]
29	Ordered chaos	[0: 0: 1]	[0: 0.25: 0.75]	[0: 0.125: 0.875]
30	Ordered disorder	[0: 0: 1]	[0: 0.375: 0.625]	[0: 0.1875: 0.8125]
31	Original copy	[0: 0.25: 0.75]	[0: 0: 1]	[0: 0.125: 0.875]
32	Passive aggressive	[0.375: 0.25: 0.375]	[0.5: 0: 0.5]	[0.4375: 0.125: 0.4375]
33	Peaceful war	[0.25: 0: 0.75]	[0: 0: 1]	[0.125: 0: 0.875]
34	Positively negative	[0.25: 0: 0.75]	[0: 0.875: 0.125]	[0.125: 0.4375: 0.4375]
35	Public secret	[0: 0.125: 0.875]	[0: 0.25: 0.75]	[0: 0.1875: 0.8125]
36	Random order	[0.125: 0: 0.875]	[0: 0: 1]	[0.0625: 0: 0.9375]
37	Restrictive freedom	[0: 0: 1]	[0: 0: 1]	[0: 0: 1]
38	Same difference	[0: 0: 1]	[0.25: 0.625: 0.125]	[0.125: 0.3125: 0.5625]
39	Seriously funny	[0.25: 0: 0.75]	[0: 0: 1]	[0.125: 0: 0.875]

40	Silent scream	[0.125: 0.375: 0.5]	[0.125: 0: 0.875]	[0.125: 0.1875: 0.6875]
41	Simple complication	[0.125: 0.375: 0.5]	[0: 0: 1]	[0.0625: 0.1875: 0.75]
42	Small crowd	[0: 0.375: 0.625]	[0: 0: 1]	[0: 0.1875: 0.8125]
43	Sophisticated naïveté	[0.625: 0: 0.375]	[0.25: 0.375: 0.375]	[0.4375: 0.1875: 0.375]
44	Strangely familiar	[0.25: 0: 0.75]	[0.25: 0.125: 0.625]	[0.25: 0.0625: 0.6875]
45	Sweet sorrow	[0.875: 0: 0.125]	[0: 0.625: 0.375]	[0.4375: 0.3125: 0.25]
46	Theoretical experience	[0: 0: 1]	[0.5: 0.375: 0.125]	[0.25: 0.1875: 0.5625]
47	Tragic comedy	[0: 0.625: 0.375]	[0: 0: 1]	[0: 0.3125: 0.6875]
48	True myth	[0.5: 0.375: 0.125]	[0: 0: 1]	[0.25: 0.1875: 0.5625]
49	Unpopular celebrity	[0.125: 0.125: 0.75]	[0.25: 0.25: 0.5]	[0.1875: 0.1875: 0.625]
50	Working holiday	[0.125: 0: 0.875]	[0: 0: 1]	[0.0625: 0: 0.9375]

I grouped the sentiment scores of these words into a similar categorization as seen earlier, but with an additional category of words that are both negative and neutral, and these words have their negative and objective scores being equal and greater than the positive score. This is shown in Table 21.

Table 21: Sentiment Distribution of Modified Words

S/N	CATEGORY	NO OF MODIFIED WORDS	TOTAL
1	Totally neutral	24	48%
2	Largely neutral	11	22%
3	Largely positive	3	6%
4	Largely negative	7	14%
5	Positive and negative	1	2%
6	Positive and neutral	2	4%
7	Negative and neutral	2	4%
	Total	50	100%

The sentiment distribution of the oxymorons under consideration as per the evaluation from SWN is presented in Table 22.

Table 22: Sentiment Distribution of Oxymorons

S/N	CATEGORY	NUMBER OF OXYMORONS	TOTAL
1	Neutral	41	82%
2	Positive	3	6%
3	Negative	4	8%
8	Positive and neutral	1	2%
9	Negative and neutral	1	2%
	Total	50	100%

Comparing the results in Tables 19 and 20 to Tables 7 and 17, it is clear that SWN has, in its rating system, a large number of words being rated as neutral (Figure 7). Further research will be needed to examine more words ion SWN.

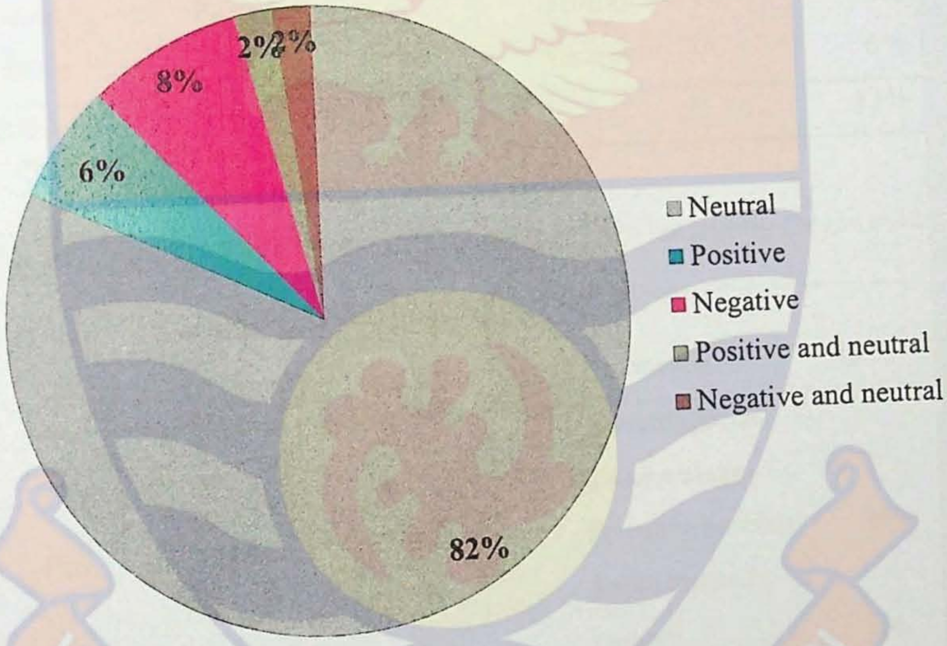

Figure 7: Total Sentiment Classification for Oxymorons

Tables 23 and 24 present the distribution of word combinations that give rise to the neutral oxymorons and those that form the remaining oxymorons respectively.

Table 23: Sentiment Combinations of words that form Neutral Oxymorons

Modifier	Word	Type of oxymoron	Percentage
Negative	Positive and Neutral	Neutral	2%
Negative	Neutral	Neutral	6%
Neutral	Neutral	Neutral	58%
Neutral	Negative	Neutral	4%
Neutral	Neutral and Negative	Neutral	2%
Neutral	Positive	Neutral	4%
Positive	Neutral	Neutral	6%
Total			82%

Table 24: Sentiment combinations of words that form remaining Oxymorons

Modifier	Modified Word	Type of Oxymoron	Oxymoron	%
Pos	Neg	Neg	Advantageous disadvantage, Friendly hostility	4%
Pos	Neu/Neg	Pos	Sophisticated naiveté	2%
Neg	Pos	Neg	Cruel kindness	2%
Neu	Neg	Neu/Neg	Positively negative	2%
Pos	Neg	Pos	Sweet sorrow	2%
Pos/Neu	Pos/Neu	Pos/Neu	Passive aggressive	2%
Pos/Neg	Neg	Neg	Objective opinion	2%
Pos	Pos/Neg	Pos	Clever foolishness	2%
Total				18%

There were 20 cases (constituting 40%) of the cases in which the polarity of the modifier differed from the polarity of the word. Of these, the modifier determined the final polarity of the oxymoron in 10 cases (20%), and the word in 9 cases (18%). The last case (2%) had an equal mix of the polarities of the modifier and the word. There is therefore no clear pattern regarding the effect of the polarity of the modifier on the oxymoron as a whole, and also which of the two words has a greater impact on the final polarity of the oxymoron.

b) If oxymorons are isolated, do they present the same effect as when used in sentences? (Does context matter?)

Chomsky (1957), as a way of making a distinction between grammar and meaning, showed that a syntactically correct sentence may be semantically useless, and a classic example of this phenomenon is

Colourless green ideas sleep furiously.

It is therefore important to move beyond the linguistic elements of a piece of text as a way of extracting meaning, and rather aim at going beyond the scope of mere grammar to examining the full situational context which includes subjective beliefs and a knowledge set of the world. Werth (1999) explains that the context of any piece of language comprises its surrounding words, and can be as little as the set of words immediately before and after, or as large as the whole universe including past and future words and pieces of text. This analogy is applicable in the case of the use of oxymorons.

The oxymorons listed in Table 17 as well as their example sentences, were analysed by our Intuitive Sentiment Rating (ISR), which, based purely on intuition, evaluates whether an oxymoron is negative, positive or neutral when used in isolation. The same test was carried out on the oxymorons used within the sentences, with the aim of getting the contextual ISR of the oxymoron, and not the sentiment of the whole text. The results are presented in Table 25.

Table 25: Comparing Oxymoron Sentiment ratings in isolation and in context

S/N	OXYMORON	SENTENCE	ISR Isolated	ISR in Context	SWN Isolated
1	Advantageous disadvantage	Being female can be an advantageous disadvantage in some specialized fields.	Pos	Pos	Neg
2	Alone together	They couldn't wait to get away alone together	Neu	Pos	Neu
3	Beautifully ugly	That Persian rug is beautifully ugly.	Neg	Neg	Neu
4	Bitter sweet	A wave of bitter sweet memories washed over her.	Neu	Neu	Neu
5	Blind sight	A lethargic demeanour is an easy way to blind sight the unethical and illegal act of bribery.	Neg	Neg	Neu
6	Clever foolishness	An oxymoron is simply clever foolishness	Pos	Neu	Pos
7	Constant variable	The value of a constant variable does not change	Neu	Neu	Neu

8	Cruel kindness	Forcing your child to wake up early in order to attend school may be seen by some as an act of cruel kindness.	Pos	Neg	Neg
9	Dark light	There is an eerie dark light around him.	Neg	Neg	Neu
10	Deafening silence	After her verbal tirade, the room filled with a deafening silence	Neg	Neu	Neu
11	Deeply superficial	Akosua has deeply superficial moral values	Neg	Neg	Neu
12	Definitely maybe	I will definitely maybe travel the world when I go on retirement.	Neu	Neu	Neu
13	Faithfully unfaithful	Being faithfully unfaithful kept him falsely true	Neg	Neg	Neu
14	Falsely true	His honour rooted in dishonour, and faith unfaithful kept him falsely true	Neg	Neg	Neu
15	Farewell reception	She had recently been invited to a farewell reception.	Pos	Neu	Neu
16	Fine mess	She left a fine mess in the room	Pos	Neg	Neu

17	Free prisoner	Serving as a house help is akin to being a free prisoner.	Neg	Neg	Neu
18	Friendly hostility	He appeared to be joking even though he cut her to size by his remarks - a clear case of friendly hostility.	Neg	Neg	Neg
19	Genuine imitation	This is a genuine imitation iPhone X	Neg	Neg	Neu
20	Honest lie	The politician was caught up in an honest lie.	Neg	Neg	Neu
21	Living dead	His dirge was enough to let the living dead walk.	Neg	Pos	Neu
22	Love hate	Theirs is a real love hate relationship	Neg	Neg	Neu
23	Minor crisis	He couldn't help her because he was involved in his own minor crisis	Neg	Neg	Neu
24	new antique	I just acquired a new antique	Neu	Pos	Neu
25	Objective opinion	I wish I could get his objective opinion	Neu	Neu	Neg
26	Old news	The story is old news	Neu	Neu	Neu
27	Only Choice	It looks like taking the bus is your only choice.	Neu	Neu	Neu

28	Openly closed	The exhibition was openly closed to the public.	Neu	Neu	Neu
29	Ordered chaos	Her closet is a true depiction of ordered chaos.	Pos	Neu	Neu
30	Ordered disorder	The room was put into an ordered disorder to create a natural effect.	Pos	Neu	Neu
31	Original copy	You are required to submit original copies of your documents to the embassy	Neu	Neu	Neu
32	Passive aggressive	Kwabena has a passive aggressive personality	Neg	Neg	Pos/Neu
33	Peaceful war	Is there such a thing as a peaceful war?	Neg	Neg	Neu
34	Positively negative	It is positively negative to hammer on only the faults of others.	Neg	Neg	Neg/Neu
35	Public secret	The family's past is a public secret	Neu	Neg	Neu
36	Random order	The codes for the buttons were generated in a random order.	Neu	Neu	Neu

37	Restrictive freedom	Being under house arrest is the same as living a life of restrictive freedom	Neg	Neg	Neu
38	Same difference	Sending Joyce or Gifty is the same difference in my opinion.	Neu	Neu	Neu
39	Seriously funny	That Nigerian movie is seriously funny	Pos	Pos	Neu
40	Silent scream	Didi's mouth opened in a silent scream	Neg	Neg	Neu
41	Simple complication	Having a baby as a teenager is a simple complication to one's future.	Neg	Neu	Neu
42	Small crowd	A small crowd had gathered at the scene of the accident	Neu	Neu	Neu
43	Sophisticated naïveté	Sophie has an air of sophisticated naiveté about her.	Neg	Neu	Pos
44	Strangely familiar	The flight attendant looks strangely familiar	Neu	Neu	Neu
45	Sweet sorrow	Parting is such sweet sorrow	Neg	Neu	Pos
46	Theoretical experience	It is recommended that you put your theoretical experience into practice in order	Neu	Neu	Neu

		to make headway in your field of expertise.			
47	Tragic comedy	We laughed through the tragic comedy	Pos	Pos	Neu
48	True myth	The movie Is based on a true myth	Neu	Neu	Neu
49	Unpopular celebrity	Audrey has managed to become an unpopular celebrity	Neg	Neg	Neu
50	Working holiday	My trip to the Caribbean was very much a working holiday	Neu	Neu	Neu

In the case of the isolated rating, ISR and SWN agreed about the sentiment on 38% of the oxymorons, 8% were in direct contrast (positive and negative), and 54% were a combination of a neutral value as against either a negative or positive sentiment.

In the case of the ISR isolated as against ISR in context, there was a 72% agreement on sentiment, 6% direct contrast, and the remaining 22% were a combination of a neutral sentiment and either a negative or a positive sentiment. The oxymorons that directly contrasted were *cruel kindness, fine mess* and *living dead*. *Cruel kindness* was intuitively rated positive with the idea that the main word under consideration is *kindness* and that *cruel* was just showing some type of kindness that was being exhibited. However, when seen within the example sentence *Forcing your child to wake up early in order to attend school* *may be seen by some as an act of cruel kindness*, it appears as a negative sort of kindness, taking into consideration some of the surrounding words like *forcing*, and was therefore rated as negative, bringing it into direct contrast from the isolated rating. Again, in the oxymoron *living dead*, it was taken that *dead* was the main word being modified by *living*, and *dead* is intuitively not a good thing, so it was rated negative. However, when read in the sentence *His dirge was enough to let the living dead walk*, *living dead* didn't sound bad at all since they were now up and walking. That therefore gave it an overall positive rating, bringing it into direct contrast.

In comparing the ISR in context with SWN in isolation, there was 42% agreement, 2% direct contrast, and 56% was a combination of a neutral sentiment and either a positive or a negative sentiment. These are shown in Figure 8.

The highest agreement was achieved when comparing the ISR in isolation and the ISR in context. The lowest contrast was however between SWN and the ISR in context. I suggest that our intuitions seem to be more useful in evaluating sentiment since there is a higher agreement between isolated and contextual cases, and this calls into question the value of the human tagging done for SWN.

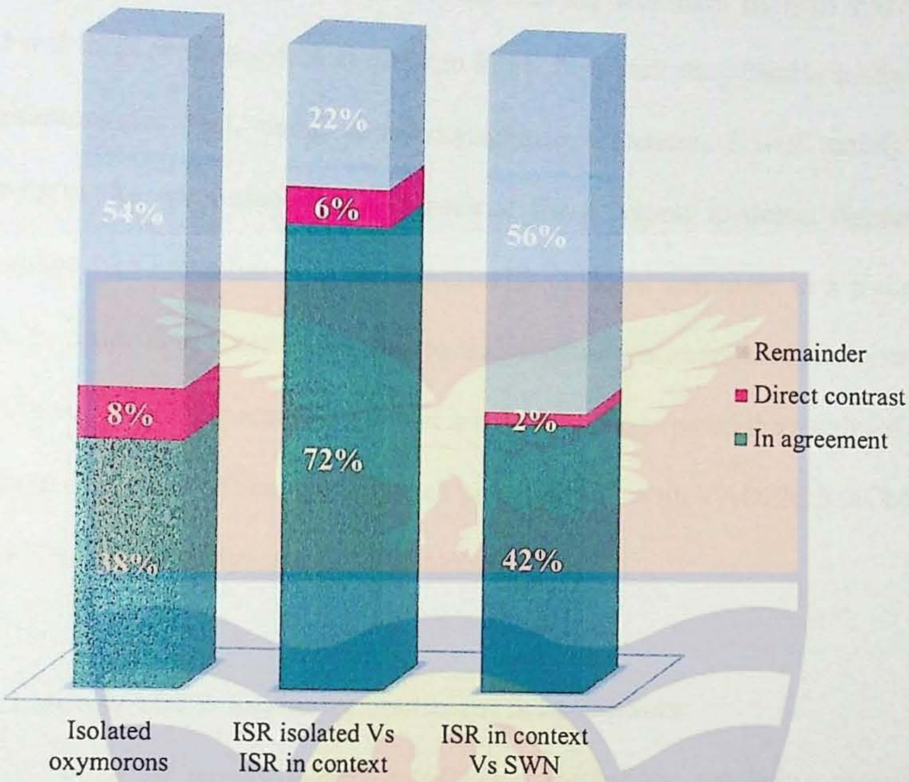

Figure 8: Oxymorons in Isolation Versus in Context using ISR and SWN

4.3.4 Summary

It was realized that in some cases, the removal of the modifier in some two-word oxymorons greatly altered the meanings of the sentences in which they occurred. These modifiers were found to have inherent sentiment values since they are essentially like any ordinary word. I concluded that there is no clear pattern regarding the effect of the polarity of the modifier on the oxymoron as a whole. There was a high agreement in comparing the intuitive sentiment rating of the oxymoron in context and the SentiWordNet evaluation of the oxymoron in isolati

4.4 Analysis of some Existing Sentiment Analysis Systems

In this section I will look at some existing sentiment analysis systems, and test them with our data in order to know how well they handle sentiment evaluations for text, using some metaphoric sentences. I will mainly be attempting to determine if it is beneficial for a system to detect figurative language like metaphor in order to correctly evaluate sentiment in a piece of text. In order to evaluate the extent to which other sentiment analysis systems fare in evaluating the sentiment in metaphoric text, I compared the results of our manual evaluation of sentiment in such pieces of text, with VADER, ItenCheck, Free Sentiment Analyzer, and MonkeyLearn.

4.4.1 How VADER Evaluates Sentiment in Metaphors.

A set of twenty manually-inspected metaphors, ten being manually designated as negative and ten being manually designated as positive, were used in sentences and given to VADER to evaluate. The compound[2], negative, neutral and positive scores were obtained. The compound score is a normalised and weighted composite score which can be used in cases like ours where a single measure of sentiment is more appropriate for analysis. It is calculated by applying a function $\frac{x}{\sqrt{x^2+\propto}}$ where x is the sum of all the sentiment scores of the sentiment-laden words, and $\propto$ is a normalised value of 15. For the purposes of comparison and evaluation, these twenty sentences have been re-written in non-

[2] A more detailed description of how VADER works is outlined in section 3.8 of Chapter 3.

metaphoric English by replacing the metaphor of interest with the basic intended meaning, even though it is difficult to remove all metaphoricity. For example, the metaphoric sentence *My great aunt kicked the bucket* was rephrased as *My great aunt died*. Again, *I have been caught between a rock and a hard place* was re-phrased as *I have been faced with two equally undesirable alternatives*. Each sentence, PM^i for *Positive Metaphors* and NM^i for *Negative Metaphors,* has its representative paraphrased meaning pair denoted by PMS^i and NMS^i respectively, where i is the serial number of the sentence. These sentences and their re-phrased versions have been outlined in Table 26 and Table 27.

Table 26: Positive Metaphorical Sentences and their Equivalent non-Metaphoric Sentences

	POSITIVE		
	METAPHORIC SENTENCE		PARAPRASED VERSION
PM1	Anita is jumping for joy at the news.	PMS1	Anita is extremely happy at the news
PM2	The information lifted his spirits	PMS2	The information made him more cheerful
PM3	Her ship has come in.	PMS3	She has suddenly become rich and successful
PM4	She had a laugh in a sea of sadness	PMS4	She found hope in the impossible situation
PM5	He swims in a sea of diamonds	PMS5	He has a lot of wealth
PM6	This is the story of a billionaire's meteoric rise from grass to grace.	PMS6	This is the story of a billionaire's transition from poverty to wealth.
PM7	He has the heart of a lion	PMS7	He has exceptional courage and fortitude
PM8	She is a light in the sea of darkness	PMS8	She is hope in a difficult situation
PM9	His voice is music to my ears	PMS9	I am pleased to hear is voice.
PM10	It is a land flowing with milk and honey	PMS10	It is a land filled with all good things.

Table 27: Negative Metaphorical Sentences and their Equivalent Non-Metaphoric Sentences

	NEGATIVE		
	METAPHORIC SENTENCE		PARAPRASED VERSION
NM[1]	After the situation was resolved, he was left high and dry	NMS[1]	After the situation was resolved, he was left in a difficult situation without any help.
NM[2]	My great aunt kicked the bucket.	NMS[2]	My great aunt died
NM[3]	Henry was so peeved that he shot the messenger	NMS[3]	Henry was so angry that he blamed the carrier of the bad news.
NM[4]	I have been caught between a rock and a hard place	NMS[4]	I have been faced with two equally undesirable alternatives
NM[5]	I realized I had been taken for a ride	NMS[5]	I realized I had been deliberately misled.
NM[6]	She cut him down with her words	NMS[6]	She reduced his self-importance with her words
NM[7]	They look down on everyone who is not as rich as they are	NMS[7]	They despise anyone who is not as rich as they are.
NM[8]	He is constantly on edge	NMS[8]	He is constantly anxious
NM[9]	He seems very down about the whole experience.	NMS[9]	He seems very depressed about the whole experience
NM[10]	He is up the river without a paddle	NMS[10]	He is in an unfortunate situation with no preparation and no resource to remedy the situation.

VADER was used to extract sentiment for each of the sentences in Table 26 and Table 27, and these results are outlined in Table 28 and Table 29. In order to represent the data in a more readable format, a 9-point scale was used to represent the various compound scores obtained from VADER, ranging from -8 for extremely negative, to +8 for extremely positive, and zero being neutral. The original VADER scores that are between -1 and +1 were distributed on the new scale as shown in Table 30, considering the fact that the compound score on VADER is to four decimal places.

Table 28: VADER Sentiment Scores for Sentences in Table 26

POSITIVE METAPHORS					PARAPHRASED VERSION				
Sentence	Compound Value	Negative Value	Neutral Value	Positive Value	Sentence	Compound Value	Negative Value	Neutral Value	Positive Value
PM1	0.5859	0.0	0.648	0.352	PMS1	0.6115	0.0	0.6	0.4
PM2	0.0	0.0	1.0	0.0	PMS2	0.5849	0.0	0.560	0.431
PM3	0.0	0.0	1.0	0.0	PMS3	0.8126	0.0	0.403	0.597
PM4	0.1779	0.252	0.435	0.313	PMS4	0.4404	0.0	0.674	0.326
PM5	0.0	0.0	1.0	0.0	PMS5	0.4939	0.0	0.556	0.444
PM6	0.4215	0.0	0.797	0.203	PMS6	-0.0256	0.213	0.581	0.206
PM7	0.0	0.0	1.0	0.0	PMS7	0.4939	0.0	0.61	0.39
PM8	-0.25	0.222	0.778	0.0	PMS8	0.1027	0.266	0.426	0.309
PM9	0.0	0.0	1.0	0.0	PMS9	0.4404	0.0	0.633	0.367
PM10	0.0	0.0	1.0	0.0	PMS10	0.4404	0.0	0.707	0.293

0.0001 – 0.1250	1
0.1251 – 0.2500	2
0.2501 – 0.3750	3
0.3751 – 0.5000	4
0.5001 – 0.6250	5
0.6251 – 0.7500	6
0.7501 – 0.8750	7
0.8751 – 1.0000	8

Using this new scale to re-define the data in Table 26 and Table 27, I achieve the following results:

Table 31: Re-defined Compound Scores for Positive Metaphors

POSITIVE METAPHORS			PARAPHRASED VERSION		
Sentence	Compound Value	New Value	Sentence	Compound Value	New Value
PM^1	0.5859	5	PMS^1	0.6115	5
PM^2	0.0	0	PMS^2	0.5849	5
PM^3	0.0	0	PMS^3	0.8126	7
PM^4	0.1779	2	PMS^4	0.4404	4
PM^5	0.0	0	PMS^5	0.4939	4
PM^6	0.4215	4	PMS^6	-0.0258	-1
PM^7	0.0	0	PMS^7	0.4939	4
PM^8	-0.25	-2	PMS^8	0.1027	1
PM^9	0.0	0	PMS^9	0.4404	4
PM^{10}	0.0	0	PMS^{10}	0.4404	4

From Table 31, VADER evaluated 3 out of the 10 metaphoric sentences correctly, representing 30% accuracy, 60% was evaluated as neutral while the remaining 10% was evaluated as negative. The reason for the low accuracy is that VADER is not designed to identify, interpret or evaluate metaphors. For the paraphrased versions of the positive metaphors, VADER correctly evaluated 90% as positive, with 10% being incorrectly evaluated as negative.

Table 32: Re-defined Compound Scores for Negative Metaphors

NEGATIVE METAPHORS			PARAPHRASED VERSION		
Sentence	Compound Value	New Value	Sentence	Compound Value	New Value
NM^1	0.1779	2	NMS^1	-0.4692	-4
NM^2	0.6249	5	NMS^2	0.128	2
NM^3	0.0	0	NMS^3	-0.8966	-8
NM^4	-0.1027	-1	NMS^4	-0.4404	-4
NM^5	0.0	0	NMS^5	0.0	0
NM^6	-0.2732	-3	NMS^6	0.0	0
NM^7	-0.4449	-4	NMS^7	-0.6832	-6
NM^8	0.0	0	NMS^8	-0.25	-2
NM^9	0.0	0	NMS^9	-0.5563	-5
NM^{10}	0.0	0	NMS^{10}	-0.7506	-7

For the negative metaphors as presented in Table 32, VADER correctly evaluated 30% of the metaphoric sentences as negative. For the paraphrased version, VADER correctly evaluated 70% as negative. For both the negative and positive metaphoric sentences under review, VADER had higher accuracy on the paraphrased versions, which suggests that it may not have the ability to evaluate metaphoric language.

This is not to say that it is not a good sentiment analyser, but that, a bit more tweaking of its operation is needed in order to score sentiment in non-metaphoric language with a higher accuracy. In some peculiar instances, the intended meaning could not be evaluated. *I realised I had been deliberately misled* and *She reduced his self-importance with her words* were scored as neutral when they are clearly negative. In these two sentences, all the constituent words have been rated as neutral, i.e., 'I', 'realised', 'I', 'had', 'been', 'deliberately', 'misled' 'She', 'reduced', 'his', 'self-importance', 'with', 'her', 'words'. Both sentences therefore are scored with an absolute neutral value of 1. There are also instances when the polarity is completely flipped. For example, *My great aunt died* is scored as positive. With the breakdown, 'great" is scored as highly positive with a compound score of 0.6249, while 'died' is cored as negative with a compound score of -0.5574. *My* and *aunt* are scored as neutral.

Though VADER incorrectly analyses metaphoric sentences, let us assume that the sentiment results of a statement like *It was a stormy meeting* as neutral is correct. I attempted to find a pattern in evaluation by adding a number of different modifiers. The results of evaluating the isolated modifiers are presented in Table 33. I then add these modifiers to our sentence *It was a stormy meeting* and outline the results in Table 34 and Figure 9.

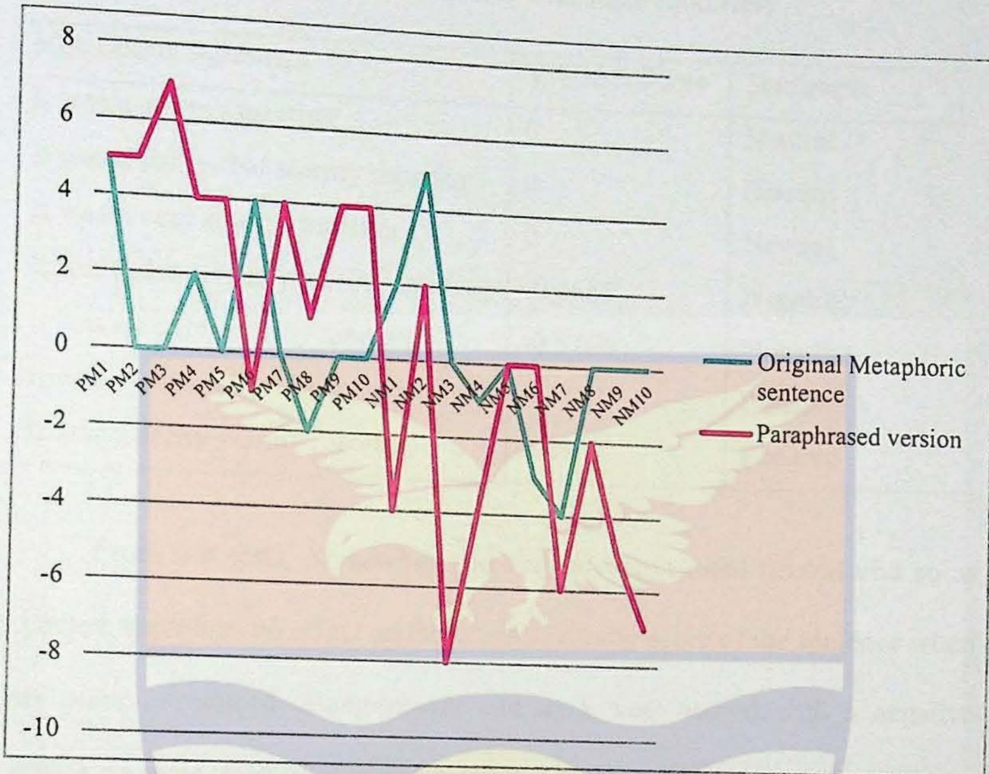

Figure 9: Original Metaphorical Sentence Score versus Paraphrased Version Score

Table 33: VADER scores for some modifiers

Word	VADER Score	Sentiment
Somewhat	0	Neutral
Very	0	Neutral
Dangerously	-0.4588	Negative
Ugly	-0.5106	Negative
Pleasantly	0.4767	Positive
Pretty	0.4939	Positive

Table 34: VADER Scores for metaphors with some modifiers

Metaphoric statement	VADER Score	Sentiment
It was a stormy meeting	0	Neutral
It was a somewhat stormy meeting	0	Neutral
It was a very stormy meeting	0	Neutral
It was a dangerously stormy meeting	-0.4588	Negative
It was an ugly, stormy meeting	-0.5106	Negative
It was a pleasantly stormy meeting	0.4767	Positive
It was a pretty stormy meeting	0.4939	Positive

From our tests, ***Somewhat*** and ***very*** are both rated neutral and so as expected, there was no effect on the overall polarity score of the sentence when they were introduced. ***Dangerously*** and ***ugly*** were scored with a negative valence on their own, and so as expected, reflected the negative sentiment on the overall sentence. Both ***pleasantly*** and ***pretty*** were classified as positive sentiments when scored on their own, and as expected, made the metaphor score positively with the same positive value when added. It can be suggested therefore that, even though VADER is unable to correctly identify and evaluate sentiment in metaphors, it is able to capture the sentiment of the modifiers that are used within the metaphor.

4.4.2 How ITENCHECK Evaluates Sentiment in Metaphors

ItenCheck is a lexicon-based sentiment API that uses a text analysis engine that has been designed to display information about different communication styles as shown in Figure 10. It aids with easy identification of intent, emotions and attitude that may be present within a piece of text, and has a feature for predicting whether or not a text is sincere. It offers 7 groups of different categories, and displays result values over Emotions (joy, surprise, anger, sadness, disgust, fear), Attitudes (positive-negative, active-passive, strong-weak), Communication style (visual, auditory, kinaesthetic, rational), Insincerity (measured on a 0-100 scale, with 0 being absolutely sincere and 100 being absolutely insincere), Timeline (past, present, future), Motivation (away – moving away from something; towards – moving towards something), and Perceptual Positions (I – I, mine self; II – he, she his, her, one, you, yours; III – them, they, their; IV – us, we, our).

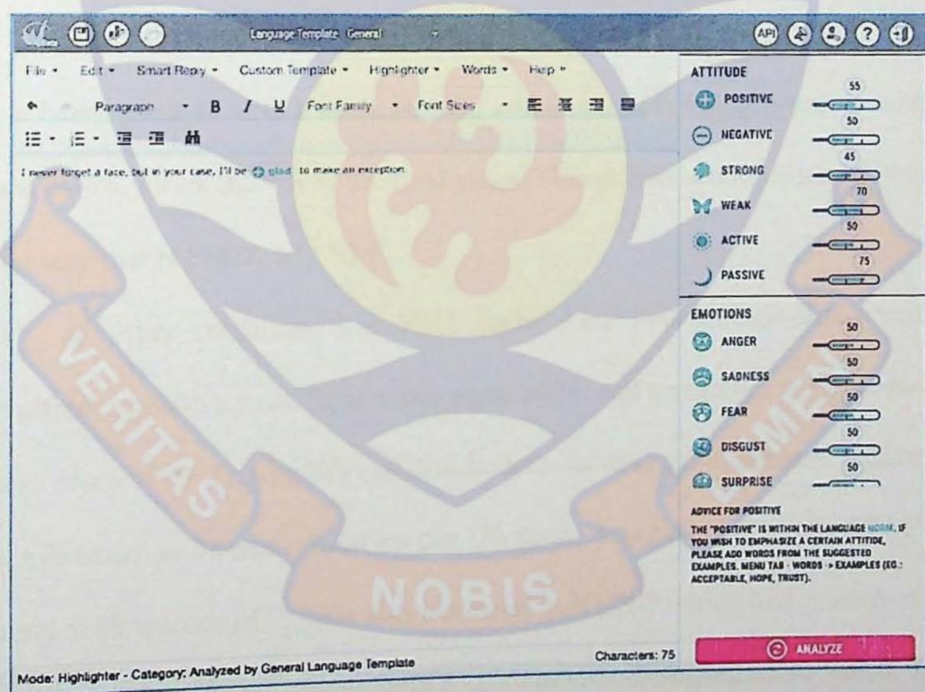

Figure 10: Interface for ItenCheck

Reference: https://www.itencheck.com

For the purposes of our study, I am interested in the Attitudes as evaluated by ItenCheck, which gives us ratings that are classified into Positive, Negative or Neutral, each rating having a score attached if that is the resulting evaluation. It does this evaluation by identifying attitude-laden pieces of text within a sentence, and scoring them, making it possible to have negative, neutral and positive words in one sentence. ItenCheck ignores scores for Neutral words and presents the scores for the positive and negative words. In the cases where there were both positive and negative words, I chose the highest score as the final attitude. For example, in sentence PMS[1], I had a score for *happy* as +75, and a score for *extremely* as -76 and so I maintained the -76 as the final score for that sentence. I did this with the assumption that, if I were to undertake a simple mean calculation, the result would be negative. Again, in PMS[4], I had *hope* being positive with a score of +75, and *impossible* being negative with a score of -76. I took the -76 as the final score. This phenomenon occurred in two other statements PMS[8], and NM[7].

In other situations, like PM[8], there were two attitude-laden words identified: a positive word *light* with a score of 70, and a negative word *darkness* with a score of 70. To simplify and standardize our evaluation scheme, I allowed the +70 score to be neutralised by the -70 score, bringing the value of PM[8] to neutral with a score of 0. This also occurred in NMS[10] which had *remedy* with a score of +53, and *unfortunate* with a score of -53. Resulting score was 0. The results obtained from ItenCheck have been presented in Table 35 and Table 36.

Table 35: Evaluation of Positive Metaphoric sentences and their Paraphrased Versions with ItenCheck

POSITIVE					
	METAPHORIC SENTENCE	Attitude Score		PARAPHRASED VERSION	Attitude Score
PM1	Anita is jumping for joy at the news.	72	PMS1	Anita is extremely happy at the news	-76
PM2	The information lifted his spirits	0	PMS2	The information made him more cheerful	79
PM3	Her ship has come in.	0	PMS3	She has suddenly become rich and successful	97
PM4	She had a laugh in a sea of sadness	-95	PMS4	She found hope in the impossible situation	-76
PM5	He swims in a sea of diamonds	0	PMS5	He has a lot of wealth	0
PM6	This is the story of a billionaire's meteoric rise from grass to grace.	57	PMS6	This is the story of a billionaire's transition from poverty to wealth.	-62
PM7	He has the heart of a lion	75	PMS7	He has exceptional courage and fortitude	100
PM8	She is a light in the sea of darkness	0	PMS8	She is hope in a difficult situation	-76
PM9	His voice is music to my ears	0	PMS9	I am pleased to hear his voice.	75
PM10	It is a land flowing with milk and honey	0	PMS10	It is a land filled with all good things.	70

Table 36: Evaluation of Negative Metaphoric sentences and their Paraphrased Versions with ItenCheck

	NEGATIVE				
	METAPHORIC SENTENCE	Attitude Score		PARAPHRASED VERSION	Attitude Score
NM[1]	After the situation was resolved, he was left high and dry	64	NMS[1]	After the situation was resolved, he was left in a difficult situation without any help.	88
NM[2]	My great aunt kicked the bucket.	79	NMS[2]	My great aunt died	89
NM[3]	Henry was so peeved that he shot the messenger	-70	NMS[3]	Henry was so angry that he blamed the carrier of the bad news.	-90
NM[4]	I have been caught between a rock and a hard place	-64	NMS[4]	I have been faced with two equally undesirable alternatives	-70
NM[5]	I realized I had been taken for a ride	0	NMS[5]	I realized I had been deliberately misled.	0
NM[6]	She cut him down with her words	-76	NMS[6]	She reduced his self-importance with her words	0
NM[7]	They look down on everyone who is not as rich as they are	-60	NMS[7]	They despise anyone who is not as rich as they are.	64
NM[8]	He is constantly on edge	0	NMS[8]	He is constantly anxious	-85
NM[9]	He seems very down about the whole experience.	-73	NMS[9]	He seems very depressed about the whole experience	-73
NM[10]	He is up the river without a paddle	0	NMS[10]	After the situation was resolved, he was left in a difficult situation without any help.	0

On the whole, ItenCheck was able to correctly categorize 30% of the positive metaphors, totally flipped the polarity of 10% (from positive to negative), and graded the remaining 60% as neutral (Table 35). It successfully categorised 50% of the paraphrased English versions of the positive metaphors, flipped the polarity of 40%, and categorised the remaining 10% as neutral (Table 35). It was also able to successfully categorise 50% of the negative metaphors, flipped polarity of 20%, and categorised the remaining 30% as neutral (Table 36). It also successfully categorised 40% of the paraphrased English versions of the negative metaphors, flipped polarity of 30%, and classed the remaining 30% as neutral (Table 36). These are shown in Figure 11.

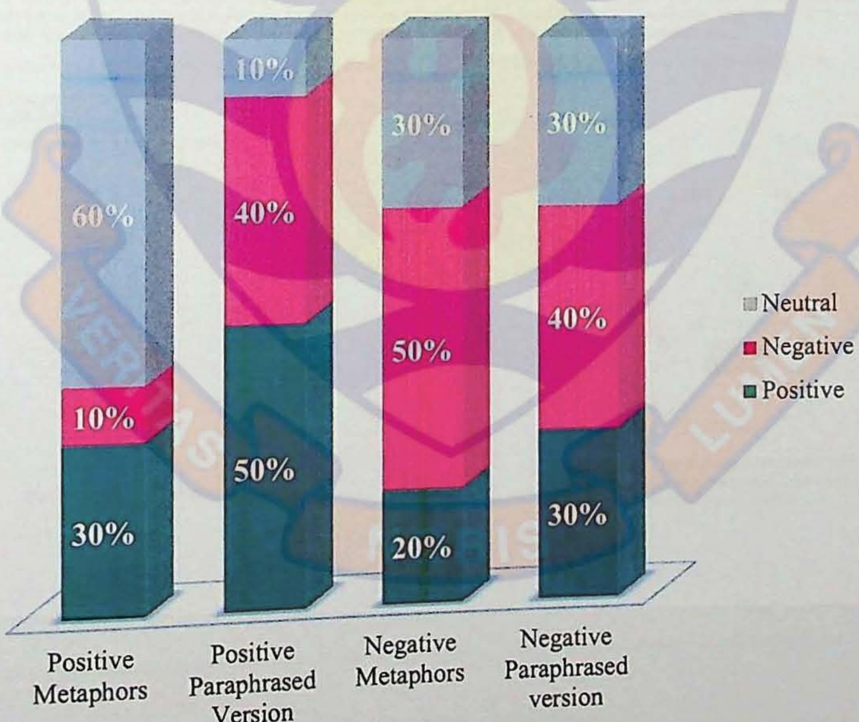

Figure 11: ItenCheck Accuracy of Evaluation of Metaphors

4.4.3 How Free Sentiment Analyzer (FSA) Evaluates Sentiment in Metaphors

FSA (figure 12) is a free tool which can be utilized for sentiment analysis on a wide variety of written English text. Sentiment is computed on a scale of -100 to +100, with -100 indicating a very negative tone, and +100 indicating a very positive tone. The interface has an area within which the text to be analysed is entered, and provides and *Analyze Test* button which then displays the sentiment on the sentiment meter. It also adds a small interpretation at the bottom of the sentiment meter.

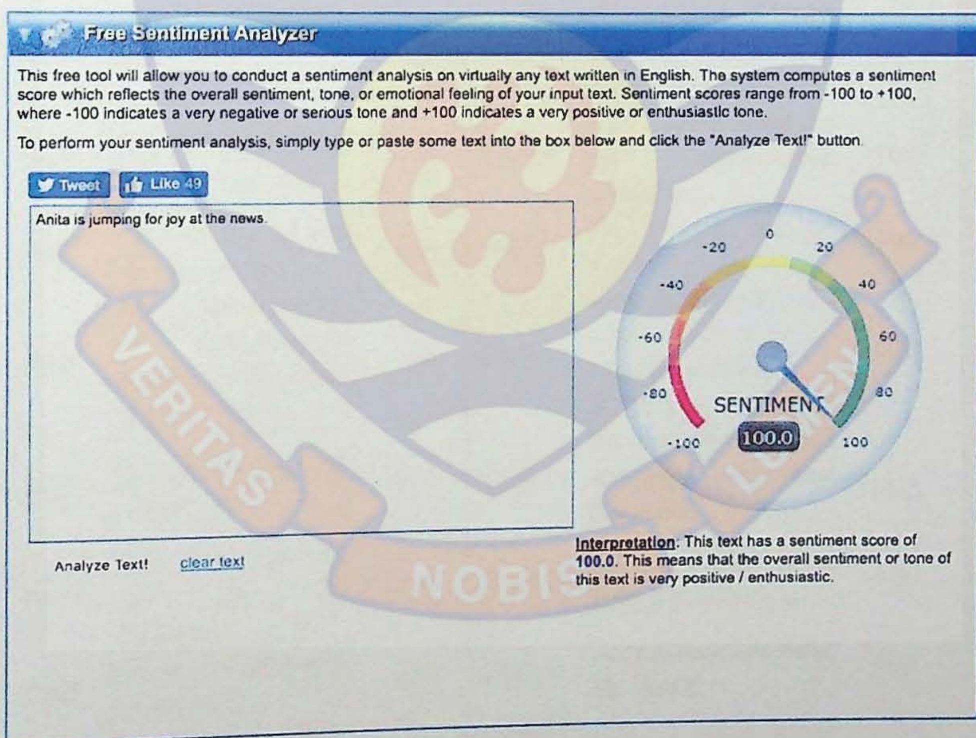

Figure 12: The Free Sentiment Analyzer Interface

Reference: https://www.danielsoper.com/sentimentanalysis/default.aspx

The same set of positive and m\negative metaphoric sentences were passed to the FSA to evaluate, and the results obtained are outlined in Table 37 and Table 38.

Table 37: Evaluation of Positive Metaphoric Sentences and their Paraphrased Versions with FSA

	POSITIVE				
	METAPHORIC SENTENCE	Score		PARAPHRASED VERSION	Score
PM1	Anita is jumping for joy at the news.	100	PMS1	Anita is extremely happy at the news	100
PM2	The information lifted his spirits	100	PMS2	The information made him more cheerful	100
PM3	Her ship has come in.	100	PMS3	She has suddenly become rich and successful	100
PM4	She had a laugh in a sea of sadness	-100	PMS4	She found hope in the impossible situation	-100
PM5	He swims in a sea of diamonds	-100	PMS5	He has a lot of wealth	-100
PM6	This is the story of a billionaire's meteoric rise from grass to grace.	100	PMS6	This is the story of a billionaire's transition from poverty to wealth.	-100
PM7	He has the heart of a lion	-100	PMS7	He has exceptional courage and fortitude	-14.2
PM8	She is a light in the sea of darkness	-100	PMS8	She is hope in a difficult situation	-100
PM9	His voice is music to my ears	100	PMS9	I am pleased to hear his voice.	100
PM10	It is a land flowing with milk and honey	100	PMS10	It is a land filled with all good things.	100

Table 38: Evaluation of Negative Metaphoric sentences and their paraphrased versions with FSA

	NEGATIVE				
	METAPHORIC SENTENCE	Attitude Score		PARAPHRASED VERSION	Attitude Score
NM1	After the situation was resolved, he was left high and dry	-100	NMS1	After the situation was resolved, he was left in a difficult situation without any help.	100
NM2	My great aunt kicked the bucket.	100	NMS2	My great aunt died	100
NM3	Henry was so peeved that he shot the messenger	-100	NMS3	Henry was so angry that he blamed the carrier of the bad news.	100
NM4	I have been caught between a rock and a hard place	100	NMS4	I have been faced with two equally undesirable alternatives	-100
NM5	I realized I had been taken for a ride	-100	NMS5	I realized I had been deliberately misled.	-100
NM6	She cut him down with her words	-100	NMS6	She reduced his self-importance with her words	-100
NM7	They look down on everyone who is not as rich as they are	-100	NMS7	They despise anyone who is not as rich as they are.	-100
NM8	He is constantly on edge	100	NMS8	He is constantly anxious	-14.2
NM9	He seems very down about the whole experience.	-100	NMS9	He seems very depressed about the whole experience	-100
NM10	He is up the river without a paddle	-100	NMS10	After the situation was resolved, he was left in a difficult situation without any help.	-100

FSA was able to correctly categorise 60% of the positive metaphoric sentences, and classed the remaining 40% as neutral. It was also able to correctly classify 50% of the paraphrased English versions of the positive metaphors and flipped polarity of remaining 50%. FSA successfully categorised 70% of the negative metaphoric sentences and flipped polarity of the remaining 30%, and was also able to successfully evaluate 70% of the paraphrased English versions of the negative metaphors while incorrectly classifying the remaining 30% as positive (Figure 13). FSA appears not to be reliable in determining sentiment in general. This could be as a result of non-optimised sentiment-extracting algorithms and lexicons in use.

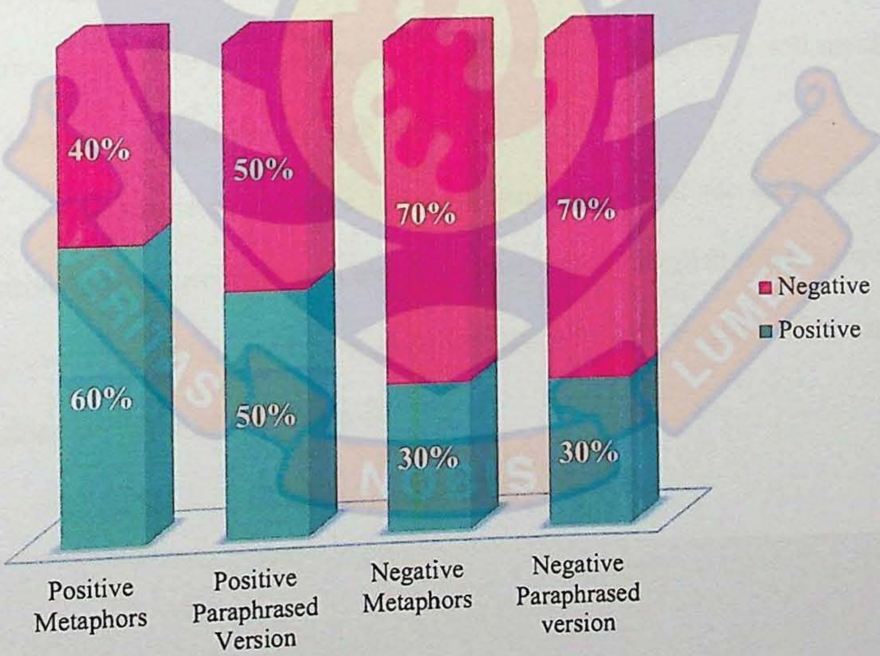

Figure 13: Free Sentiment Analyzer Accuracy of Evaluation of Metaphors

4.4.4 How MonkeyLearn Evaluates Sentiment in Metaphors

MonkeyLearn (Figure 14) is an app that offers various functionalities for making text analysis simple. One of the models on offer, which is what I have used in this project, is the Sentiment Analysis classifier, which has been trained over different domains for analysing sentiment (positive, negative, or neutral) in English text. The app has an interface which allows a user to enter text, a "Classify Text" button which submits the input text for analysis, and a window which displays the results of the classification by showing the tag (positive, negative, or neutral), and the confidence level of that classification. The confidence level shows the rating of that sentiment on a 0-100% scale. For example, *This is a great tool* has a confidence level of 99.8%, which is the same as saying that the sentence is 99.8% positive. A confidence of a negative tag with a value of 32% means that the sentence is negative, though at only a 32% degree. A sentence that has a negative confidence rating of 89% will mean that the sentence is negative to a high degree.

The results of using the MonkeyLearn app to evaluate sentiment in 10 positive metaphoric sentences and their paraphrased English pairs, as well 10 negative metaphoric sentences and their paraphrased English versions, are outlined in Table 39 and Table 40.

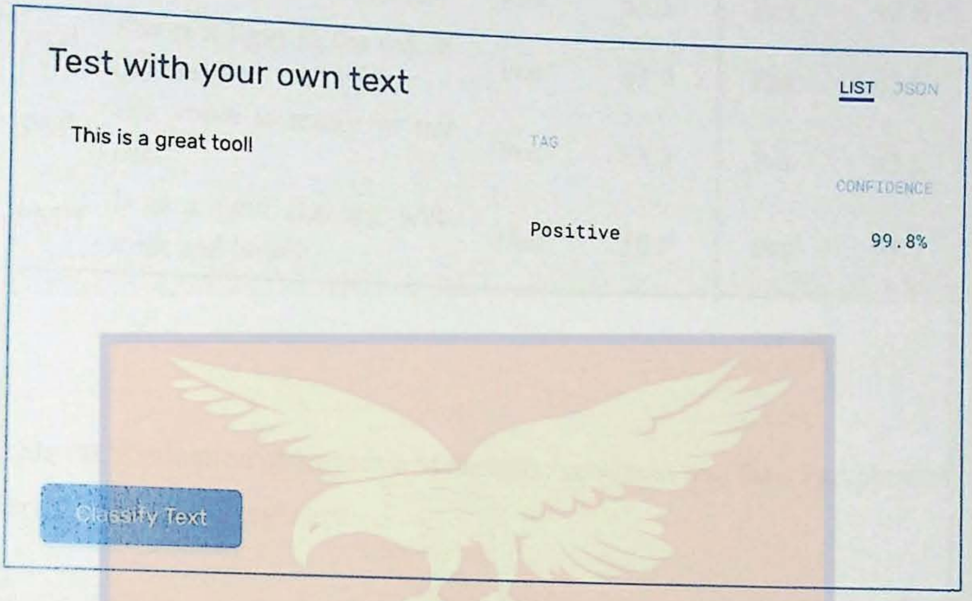

Figure 14: MonkeyLearn App interface

Reference: https://app.monkeylearn.com

Table 39: Evaluation of Positive Metaphoric Sentences and their Paraphrased Versions with MonkeyLearn

POSITIVE					
				PARAPHRASED VERSION	
	METAPHORIC SENTENCE	Tag	Confidence	Tag	Confidence
PM1	Anita is jumping for joy at the news.	Pos	68.9	Neu	65.8
PM2	The information lifted his spirits	Neu	61.1	Neu	50.3
PM3	Her ship has come in.	Neu	85.8	Pos	72.7
PM4	She had a laugh in a sea of sadness	Pos	44.9	Pos	84.6
PM5	He swims in a sea of diamonds	Neu	80.1	Neu	64.3
PM6	This is the story of a billionaire's meteoric rise from grass to grace.	Neu	55.5	Neu	56.3

PM7	He has the heart of a lion	Pos	65.5	Pos	98.8
PM8	She is a light in the sea of darkness	Pos	61.5	Pos	63.6
PM9	His voice is music to my ears	Pos	68.2	Pos	93.5
PM10	It is a land flowing with milk and honey	Neu	80.9	Pos	95.7

Table 40: Evaluation of Negative Metaphoric sentences and their Paraphrased Versions with MonkeyLearn

	NEGATIVE				
				PARAPHRASED VERSION	
	METAPHORIC SENTENCE	Tag	Confidence	Tag	Confidence
PM1	Anita is jumping for joy at the news.	Pos	70.8	Neg	88.1
PM2	The information lifted his spirits	Neu	59.7	Neu	80.3
PM3	Her ship has come in.	Neg	87.9	Neg	97.2
PM4	She had a laugh in a sea of sadness	Pos	43.2	Neu	59.3
PM5	He swims in a sea of diamonds	Neu	77	Neu	50.5
PM6	This is the story of a billionaire's meteoric rise from grass to grace.	Neu	60.1	Pos	81.2
PM7	He has the heart of a lion	Neg	72.5	Neg	85.7
PM8	She is a light in the sea of darkness	Neu	39.7	Neg	81.6
PM9	His voice is music to my ears	Pos	63.6	Neg	76.6
PM10	It is a land flowing with milk and honey	Pos	49.6	Neg	95.5

The MonkeyLearn app was able to successfully evaluated 50% of the positive metaphoric sentences and categorised the remaining 50% as neutral. It was able to correctly categorise 60% of the positive version of the paraphrased English equivalent to the metaphors, and classed the remaining 40% as neutral. It successfully categorised 20% of the negative metaphors, flipped polarity of 40%, and categorised the remaining 40% as neutral. It was also able to correctly categorised 60% of the paraphrased English versions of the negative metaphors, flipped polarity of 10%, and classified the remaining 30% as neutral. These are shown in Figure 15.

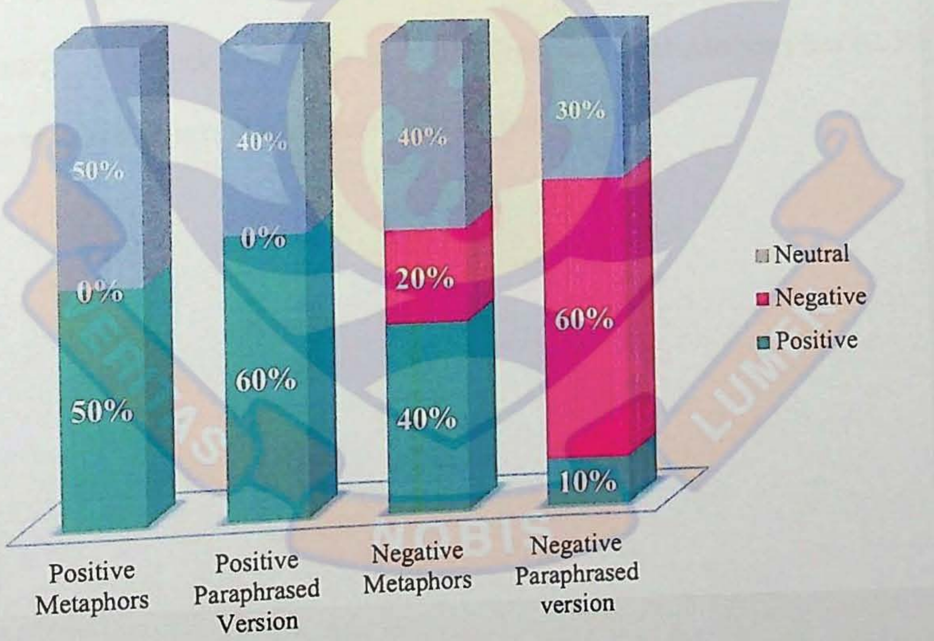

Figure 15: MonkeyLearn Accuracy of Evaluation of Metaphors

4.4.5 Comparative Analysis of Systems on Metaphors

In evaluating positive metaphors, FSA had the highest accuracy score with 60%, followed by MonkeyLearn with 50%, and then VADER and ItenCheck with 30%. With the evaluation of the paraphrased English versions of the metaphors, VADER had the highest accuracy with 90%, followed by MonkeyLearn with 60%, and ItenCheck and FSA at 50%. The evaluation of negative metaphors had FSA having the highest accuracy with 70%, ItenCheck next with 50%, VADER with 30%, and MonkeyLearn with 20% accuracy. With evaluation of the paraphrased English versions of the negative metaphors, VADER and FSA had the highest accuracy score of 70%, followed by MonkeyLearn with 60%, and ItenCheck with 40%. These are shown in Figure 16. Averagely, VADER is able to correctly evaluate sentiment with 55% accuracy, ItenCheck has 42.5% accuracy, Free Sentiment Analyzer has 62.5% accuracy, and MonkeyLearn has 47.5% accuracy.

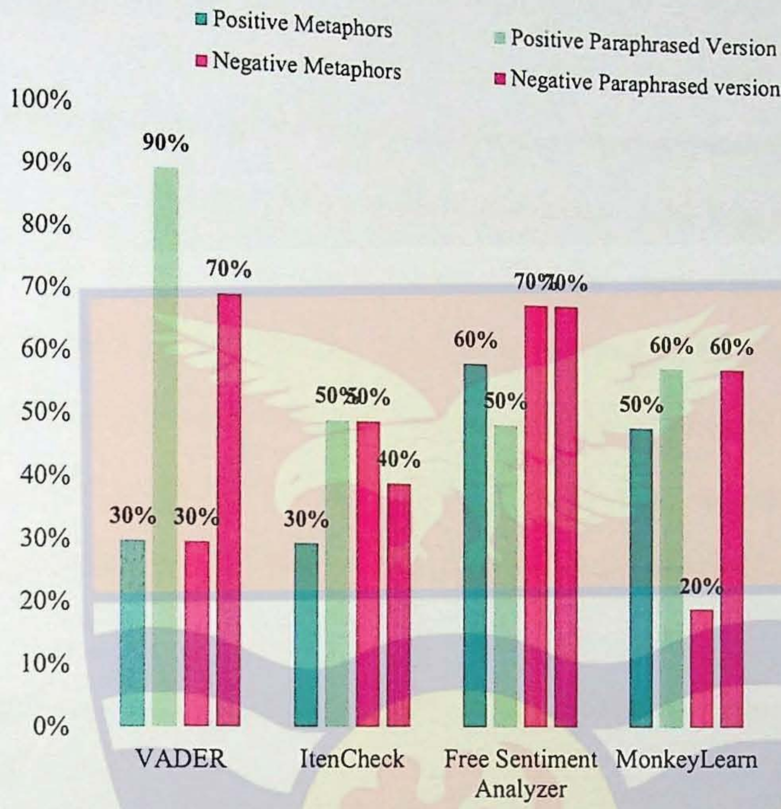

Figure 16: Comparative study of successful sentiment evaluation of Metaphors

4.4.6 Summary

It was concluded that VADER can correctly evaluate 30% of the sentiment in both negative and positive metaphors, and it is able to capture a 100% of the sentiment of modifiers used within the metaphors. ItenCheck correctly evaluated 30% of the positive metaphors and 20% of the negative ones; Free Sentiment Analyzer correctly captured 60% of the sentiment in positive metaphors and 30% of the negative metaphors; and MonkeyLearn correctly analyzed 50% of the positive metaphors and 40% of the negative metaphors,

4.5 Comparative results of sentiment evaluation of oxymorons

This section does not, in itself, answer any of the RQs, but is a follow on from section 4.3.2b which presents values for oxymorons that have been intuitively rated in isolation as well as in context, and the SWN values from the isolated oxymorons (Table 25). Four systems, SWN, VADER, MonkeyLearn and Free Sentiment Analyzer were used to evaluate the sentiment of the oxymorons listed in Table 16. The results are presented in Table 41.

Table 41: Comparative Analysis of how Systems Rate Sentiment in Oxymorons

S/N	OXYMORON	SWN	VADER	MonkeyLearn	FSA
1	Advantageous disadvantage	Neg	Neg	Neg	Neg
2	Alone together	Neu	Neg	Neu	Pos
3	Beautifully ugly	Neu	Pos	Neg	Neg
4	Bitter sweet	Neu	Pos	Neg	Pos
5	Blind sight	Neu	Neg	Neg	Pos
6	Clever foolishness	Pos	Pos	Neg	Neg
7	Constant variable	Neu	Neu	Neg	Pos
8	Cruel kindness	Neg	Neg	Neu	Neg
9	Dark light	Neu	Neu	Neu	Pos
10	Deafening silence	Neu	Neg	Neu	Neg
11	Deeply superficial	Neu	Neu	Neg	Neg
12	Definitely maybe	Neu	Pos	Neu	Neg
13	Faithfully unfaithful	Neu	Pos	Neg	Neg

14	Falsely true	Neu	Pos	Neg	Neg
15	Farewell reception	Neu	Neu	Neu	Neg
16	Fine mess	Neu	Neg	Neg	Pos
17	Free prisoner	Neu	Neg	Neg	Neg
18	Friendly hostility	Neg	Neg	Neg	Pos
19	Genuine imitation	Neu	Neu	Pos	Neg
20	Honest lie	Neu	Pos	Neg	Neg
21	Living dead	Neu	Neg	Neu	Neg
22	Love hate	Neu	Pos	Neg	Pos
23	Minor crisis	Neu	Neg	Pos	Neg
24	New antique	Neu	Neu	Neu	Pos
25	Objective opinion	Neg	Neu	Neg	Neg
26	Old news	Neu	Neu	Neu	Pos
27	Only choice	Neu	Neu	Neg	Pos
28	Openly closed	Neu	Neu	Neu	Neg
29	Ordered chaos	Neu	Neg	Neu	Pos
30	Ordered disorder	Neu	Neg	Neu	Pos
31	Original copy	Neu	Pos	Neu	Pos
32	Passive aggressive	Pos/Neu	Pos	Neg	Neg
33	Peaceful war	Neu	Neg	Neg	Neg
34	Positively negative	Neg/Neu	Neg	Neg	Neg
35	Public secret	Neu	Neu	Neu	Pos
36	Random order	Neu	Neu	Neu	Pos
37	Restrictive freedom	Neu	Pos	Neg	Pos
38	Same difference	Neu	Neu	Neu	Neg
39	Seriously funny	Neu	Pos	Pos	Neg
40	Silent scream	Neu	Neg	Neg	Neg
41	Simple complication	Neu	Neu	Pos	Neg
42	Small crowd	Neu	Neu	Pos	Neg

43	Sophisticated naïveté	Pos	Pos	Pos	Neg
44	Strangely familiar	Neu	Neg	Neg	Pos
45	Sweet sorrow	Pos	Neg	Pos	Pos
46	Theoretical experience	Neu	Neu	Neu	Neg
47	Tragic comedy	Neu	Neg	Pos	Neg
48	True myth	Neu	Pos	Pos	Neg
49	Unpopular celebrity	Neu	Neu	Neu	Neg
50	Working holiday	Neu	Pos	Neu	Pos

In 2% of the oxymorons, all four systems produced the same sentiment. In 38% of the oxymorons, 3 systems had the same result. In 48% of the oxymorons, 2 systems agreed with the other 2 having different sentiments, and in the remaining 12% of the cases, the four systems split into only 2 different sentiments. This is shown in Figure 17.

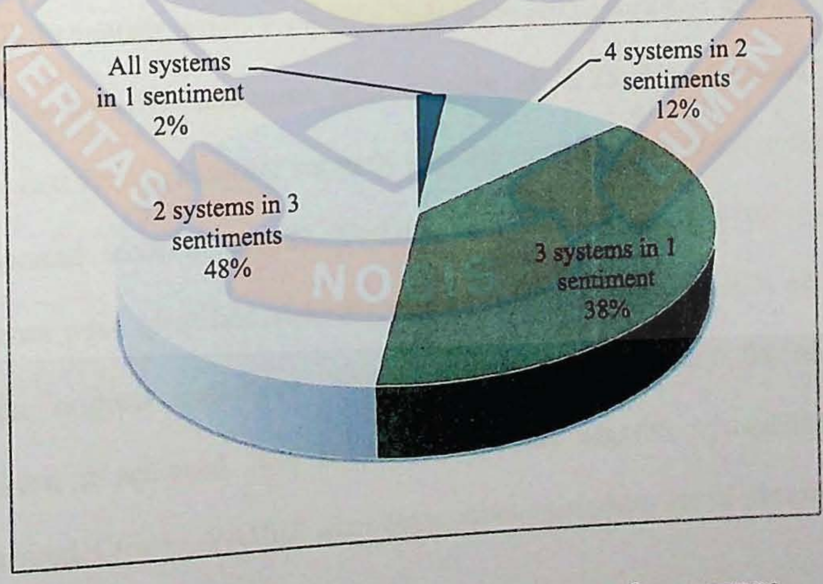

Figure 17: Comparative study of sentiment evaluation of oxymorons

4.6 Chapter Summary

In summary, it can be concluded that it is crucial to detect metaphors before sentiment is extracted. This is important because the current sentiment analysis systems are not designed to evaluate metaphors or oxymorons, even though there are separate systems for detecting metaphors. For a system to score affect to a very high accuracy, it will be beneficial to not only detect the metaphor, but also to be able to interpret it, and have the evaluation system score the interpreted sentence.

For example, in the case of VADER analysis, the metaphoric sentence *After the situation was resolved, he was left high and dry*, the score obtained was a compound value of +0.1779. From manual inspection and interpretation however, I know that being *left high and dry* is not a positive state. When I get the meaning and re-write the sentence to be *After the situation was resolved, he was left in a difficult situation without any help,* the compound score was -0.4692. The paraphrased version gave a more accurate sentiment score with VADER. In another instance, *She is a light in the sea of darkness* was evaluated to have a negative sentiment with a score of -0.25 for compound. The paraphrased version however correctly puts the sentiment as a positive one with a compound score of 0.1027. VADER had 90% accuracy when positive metaphors were identified and paraphrased, while it had only 30% accuracy with the original metaphors. With the same 30% accuracy for negative metaphors, it achieved 70% accuracy when the negative metaphors were paraphrased. Clearly, VADER does better when metaphors are re-phrased.

ItenCheck did better at evaluating the paraphrased positive metaphors (30% for metaphors, 50% for paraphrased version), but did worse on the paraphrased negative metaphors (50% for metaphors, 40% for the paraphrased versions). Since its highest accuracy score is 50% regardless of the type of sentence it may be evaluating, it will need a bit of re-working to give it a higher accuracy.

Free Sentiment Analyzer performed better on the positive metaphors than on their paraphrased versions (60% on metaphors and 50% on paraphrased versions), but had a 70% score on both the negative metaphoric sentences and their paraphrased negative versions. It is not immediately clear why it does better at evaluating negative sentiment than positive ones. Future research will analyse this.

MonkeyLearn did better on the paraphrased versions of both positive and negative metaphors, scoring 60% for each, while it had 50% score for positive metaphors and 20% for negative metaphors. Clearly, like VADER, MonkeyLearn does better when the metaphoric phrases are rephrased.

On the issue of oxymorons, it was concluded that the modifiers in the two-word oxymorons have inherent sentiment values, though there is no clear pattern on how these values affect the overall polarity of the oxymoron. There were also significant differences in some of the meanings of sentences that contained oxymorons, and their auxiliary sentences that had the modifier removed. One such example is *My trip to the Caribbean was very much a working holiday* and its auxiliary sentence *My trip to the Caribbean was very much a holiday*. I also concluded that the context within which the oxymoron occurs matters, and has an impact on the sentiment that can be inferred from the oxymoron. When four systems (VADER, SentiWordNet, MonkeyLearn and Free Sentiment Analyzer) were used to evaluate oxymorons, there was agreement in only 2% of the cases.

Future research could examine the possibility of incorporating the MIPVU or a similar set of rules that can identify metaphors and oxymorons into these systems that attempt to evaluate natural language, so as to identify and possibly rephrase before evaluating.

CHAPTER FIVE

SUMMARY, CONCLUSIONS AND RECOMMENDATIONS

5.1 Summary and Conclusions

This thesis has explored how metaphors, modifiers, oxymorons and sentiment get used altogether in communication, the effect they seem to have on each other, and just how interwoven they are.

Chapter One begun by giving a brief introduction on what the research aimed to achieve, and outlined the format of the report. The research questions that I sought to have answers to are outlined as follows:

- RQ1: To what extent do some current Sentiment Analysis systems cope with modifiers?
- RQ2: What do modifiers contribute to two-word oxymorons?
- RQ3: What do modifiers contribute to affective metaphoric communication?
- RQ4: In order for a system to detect affect, is it beneficial for it to detect metaphor and oxymoron?

In Chapter Two, I carried out an extensive research in three major domains: Metaphors, Affect and Modifiers. I saw that there are several different categorizations of metaphor, and found it wise to base our research on Lakoff and Johnson's 1980 work on conceptual metaphors, even though it has issues like assigning concepts that are not only limited to particular domains. An example of this error is the concept of *TIME IS MONEY* which has examples like *Do not waste my time*, whereas money is not the only thing that can be wasted, but rather, all manner of resources including (but not limited to) life, advice and intellect. I also used a number of other metaphors with examples like *Rita is a peacock* and *Eleanor's tears were a river flowing down her cheeks*. I then examined the MIP and the MIPVU and noted the differences in application, giving brief details on how they are applied in identifying metaphors. There has been quite a bit of work done in an attempt at automatically detecting metaphor, and these have displayed varying degrees of successes. Some of the complications that arise in the attempt to automatically detect metaphor include the need to have large sets of knowledge based on various concepts and possible mappings that could exist, which is further complicated by the use of novel metaphors as far as continuing communication is concerned, since the list of metaphors in any particular conceptual domain remains infinite. I also took an in-depth look into different approaches to detecting sentiment, and finished by defining what modifiers are and in what context they would be used throughout the remainder of the report.

Chapter Three outlined the various tools that would be used for the empirical studies in the latter stages of the research. It explained how VADER works, what constitutes WordNet and SentiWordNet and how they can be used, and then went through a sentiment analysis cycle, explaining in detail what each step would achieve.

Chapter Four was sectioned to cover studies that answered the RQs. Section 4.1 was a general introduction to the experiments that were undertaken. Section 4.2 answered RQ1 by comparing the intuitive understanding and interpretation of several adverbs of manner with the meanings as outlined in WordNet, and concluded that SentiWordNet cannot be fully relied on to give correct sentiment scores of words in general. It would therefore be suggested that SWN gets recalibrated to align meaning and sentiment scores. Adverbs like *disgracefully, harshly, shamefully* and *idiotically* have been labelled as absolute neutral adverbs with an objective score of 1, and this does not match with their various definitions of *"in a dishonourable manner or to a dishonourable degree', "in a harsh or unkind manner', "in a dishonourable manner or to a dishonourable degree"* and *"in an idiotic manner"* respectively. Other adverbs which are not labelled as absolute neutral adverbs, but still with an objective score of more than or equal to 0.75 include *stupidly, greedily, insolently, terribly, successfully, devilishly, positively, hatefully* and *deceitfully*, whose meanings in WN are *"in a stupid manner", 'in a greedy manner", 'in an insolent manner", "in a terrible manner", "with success; in a successful manner", "as a devil; in an evil manner", "so as to be positive; in a positive manner", "in a hateful manner"*, and *"in a corrupt and deceitful manner"*. I concluded that SWN does not differentiate between the cases where a writer is merely reporting a sentiment as displayed by someone or of something, and the cases where the writer is expressing his own sentiments about someone or something, and this may be a key reason why some intuitively sentiment-laden adverbs are being rated as neutral when their meanings suggest otherwise.

Section 4.3 sought to answer RQ2 by examining how the use of modifiers can give rise to oxymorons, and concluded that the inherent values of modifiers as outlined in SWN, gave rise to a number of semantic errors that I concluded as being due to a disconnect between sentiment values and interpretation. I also saw that the word being modified is the word that gives the sentence it occurs in, its basic meaning. As the word itself self implies, the modifiers only seek to modify the meaning of the main word to some extent. Again, I examined a list of oxymorons and how they are used in discourse, and concluded that it is crucial to examine the full context within which the oxymoron occurs, in order to correctly interpret it. RQ3 raised the issue of mixing metaphor and affect, and section 2.6 of Chapter 2 addressed this by conducting a theoretical analysis, examining the various ways in which modifiers can be mixed with metaphors, and the resulting effects.

Section 4.4 addressed RQ4 by using some existing sentiment analysis systems (VADER, ItenCheck, MonkeyLearn, and Free Sentiment Analyzer) to extract sentiment information from both metaphoric and oxymoronic sentences. It was concluded that these systems do not have the ability to correctly evaluate the sentiment in oxymorons and metaphors, but could get good scores for individual, non-figurative words. For example, I used VADER to attempt to extract sentiment information from metaphoric sentences that have made use of modifiers in sentences like *It was a dangerously stormy meeting*. Our expectation was that for a total semantic polarity score, the sentiment of the modifier would have an impact on that of the metaphor. This was however not the case because VADER has no ability to identify metaphor to even begin to analyse, and so every metaphor fed into it was evaluated in a literal sense, which affects the overall scores obtained.

I concluded that all the systems tested were not designed to identify metaphors and oxymorons, and that any attempted evaluation was carried out on the literal words that were used in those sentences.

My specific contribution is the identification of systemic errors in SentiWordNet including wrong sentiment tags and the omission of sentiment information on some synsets, and the deficiency in some existing SA systems which make them unable to identify, evaluate, or extract accurate sentiment-related information from figures of speech, particularly metaphors and oxymorons.

5.2 Recommendations for future work

Due to the vast variety of modifiers and the myriad ways in which they can be used in sentences, more extensive work must be done on computationally extracting sentiment from text and whole documents such that even a fine mix of sentiment will be captured.

It would also beneficial to have SA systems that can differentiate between sentiment of a writer, and the sentiment of people in a scenario under consideration. Mixing the two introduces noise into the analysis, and makes it computationally impossible to objectively extract sentiment of people in the scenarios by themselves. As I acknowledged in a sentence like *To my utter disgust, she fed her dog from her plate*, more work has to be done to enable automatic computations separate the sentiment of the writer in "*To my utter disgust*" which is oriented towards the negative emotion, from the sentiment of the person in the scenario being discussed "*she fed her dog from her plate*" which is practically neutral. Mixing them will mean that an objectively neutral sentiment has been incorrectly put across as negative (even if to a minute degree), and introduces errors which may not be easily known in the assessment of large pieces of text.

Tools like VADER which is inbuilt into python, can be enhanced greatly to give the ability to detect correct sentiment by linking it to the updated sentiment lexicon from SWN and some existing SA systems that have an appreciable degree of correct sentiment analysis. It could be further enhanced with the ability to identify metaphoric and oxymoronic text, and ignore them in evaluations if it does not have the ability to correctly interpret them. In the case of detecting oxymorons, future studies can examine special measures that could be included for combining the sentiment of the words in the detected oxymoron.

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APPENDICES

APPENDIX A

EXPRESSING NEGATIVE SENTIMENT

S/N	adverb	Sense	meaning	Sentence
1	disgracefully	r.01	in a dishonorable manner or to a dishonorable degree	his grades were disgracefully low
2	fearfully	r.02	in an alarming manner	they were fearfully attacked
3	harshly	r.02	in a harsh and grating manner	her voice fell gratingly on our ears
4	horribly	r.01	of a dreadful kind	there was a dreadfully bloody accident on the road this morning
5	recklessly	r.01	in a reckless manner) reckless (a1) - (marked by defiant disregard for danger or consequences (a2) - (characterized by careless unconcern	a reckless driver reckless squandering of public funds
6	sadly	r.01	in an unfortunate way	sadly, he died before he could see his grandchild

7	shamefully	r.01	in a dishonorable manner or to a dishonorable degree	his grades were disgracefully low
			shame (n1) - (a painful emotion resulting from an awareness of inadequacy or guilt	
			(n2) - (a state of dishonor)	one mistake brought shame to all his family
			(n3) - (an unfortunate development	it's a pity he couldn't do it
			(v1) - (bring shame or dishonor upon	he dishonored his family by committing a serious crime
			(v2) - (compel through a sense of shame)	She shamed him into making amends
			(v3) - (cause to be ashamed	
8	shockingly	r.02	very badly	they behaved shockingly at the funeral
9	stupidly	r.01	in a stupid manner	he had stupidly bought a one-way ticket

			stupid (n1) - (a person who is not very bright)	The economy, stupid!"
			(a1) - (lacking or marked by lack of intellectual acuity)	
			(a2) - (in a state of mental numbness especially as resulting from shock)	he had a dazed expression on his face"; "lay semiconscious, stunned (or stupefied) by the blow"; "was stupid from fatigue"
			(a3) - lacking intelligence	a dull job with lazy and unintelligent co-workers
10	terribly	r.02	in a terrible manner	she sings terribly
11	wantonly	r.01	in a wanton manner	the animals were killed wantonly for sport
12	woefully	r.01	in an unfortunate or deplorable manner	he was sadly neglected"; "it was woefully inadequate

APPENDIX B

REPORTING NEGATIVE SENTIMENT

S/N	adverb	Sense		
1	angrily	r.01	with anger	He angrily denied the accusation
2	brazenly	r.01	in a brazen manner	He spoke brazenly
			Brazen (v1) – face with defiance or impudence	brazen it out
			Brazen (a1): unrestrained by convention or propriety	brazen arrogance
3	covetously	r.01	with jealousy; in an envious manner	he looked at his friend's new car jealously
4	covetously	r.02	n a greedy manner	
5	deceitfully	r.01	in a corrupt and deceitful manner	he acted dishonestly when he gave the contract to his best friend
6	destructively	r.01	in a destructive manner	he is destructively aggressive
			Destructive (a) - causing destruction or much damage	a policy that is destructive to the economy", destructive criticism

7	devilishly	r.01	as a devil; in an evil manner	his writing could be diabolically satiric
8	diabolically	r.01	as a devil; in an evil manner	his writing could be diabolically satiric
9	erroneously	r.01	in a mistaken or erroneous manner Erroneous (a) - (containing or characterized by error)	he mistakenly believed it erroneous conclusions
10	fearfully	r.01	in fear Fear (n1) - an emotion experienced in anticipation of some specific pain or danger (usually accompanied by a desire to flee or fight	she hurried down the stairs fearfully
11	fiendishly	r.01	as a devil; in an evil manner	his writing could be diabolically satiric
12	foolishly	r.01	without good sense or judgment	He acted foolishly when he agreed to come
13	greedily	r.01	greedily (in a greedy manner	

			Greed (n1) - (excessive desire to acquire or possess more (especially more material wealth) than one needs or deserves) (n2) - reprehensible acquisitiveness; insatiable desire for wealth (personified as one of the deadly sins	
14	harshly	r.01	in a harsh or unkind manner	That's enough!' he cut in harshly
15	hatefully	r.01	in a hateful manner hate (n1) - the emotion of intense dislike; a feeling of dislike so strong that it demands action Hate (v1) - dislike intensely; feel antipathy or aversion towards) "I hate Mexican food	
16	idiotically	r.01	in an idiotic manner	what arouses the indignation of the honest satirist is not the fact that people in positions of power

				or influence behave idiotically
17	insolently	r.01	in an insolent manner	he had replied insolently to his superiors
			Insolent (a1) - (marked by casual disrespect	a flip answer to serious question"; "the student was kept in for impudent behavior
			(a2) - (unrestrained by convention or propriety	the modern world with its quick material successes and insolent belief in the boundless possibilities of progress"- Bertrand Russell
18	irritably	r.01	in a petulant manner	he said testily: `Go away!'
19	jealously	r.02	with jealousy; in an envious manner	he looked at his friend's new car jealously
20	madly	r.02	in an insane manner	the witch cackled madly
21	naughtily	r.01	in a disobedient or naughty way	behaved naughtily when they had guests and was sent to his room

22	negatively	r.01	in a harmful manner	he was negatively affected
23	negatively	r.02	in a negative way	he was negatively inclined
24	noisily	r.01	with much noise or loud and unpleasant sound	he blew his nose noisily
25	reluctantly	r.01	with reluctance reluctance (n2) - (a certain degree of unwillingness	a reluctance to commit himself
26	rudely	r.01	rudely (in an impolite manner	he treated her impolitely
27	sadly	r.02	with sadness; in a sad manner	She died last night,' he said sadly
28	sadly	r.03	in an unfortunate or deplorable manner	he was sadly neglected
29	sarcastically	r.01	in a sarcastic manner sarcastic (a1) - (expressing or expressive of ridicule that wounds	Ah, now we're getting at the truth,' he interposed sarcastically"
30	wantonly	r.02	in a licentious and promiscuous manner	this young girl has to share a room with her mother

				who lives promiscuously
			wanton (n1) - (lewd or lascivious woman	
			(v1) - (waste time; spend one's time idly or inefficiently)	
			(v2) - (indulge in a carefree or voluptuous way of life	
			(v3) - (spend wastefully) "wanton one's money away	
			(v4) - become extravagant; indulge (oneself) luxuriously	
			(v5) - (engage in amorous play)	
			(v6) - behave extremely cruelly and brutally	
			(a2) - (casual and unrestrained in sexual behavior)	"her easy virtue"; "he was told to avoid loose (or light) women"; "wanton behavior
31	wickedly	r.01	in a wicked evil manner	act wickedly"; "grin evilly"

wicked (a1) - (morally bad in principle or practice)	
(a2) - (having committed unrighteous acts)	a sinful person
(a3) - intensely or extremely bad or unpleasant in degree or quality)	) "severe pain"; "a severe case of flu"; "a terrible cough"; "under wicked fire from the enemy's guns"; "a wicked cough"
(a4) - (naughtily or annoyingly playful)	"teasing and worrying with impish laughter"; "a wicked prank"
(a5) - (highly offensive; arousing aversion or disgust)	"a disgusting smell"; "distasteful language"; "a loathsome disease"; "the idea of eating meat is repellent to me"; "revolting food"; "a wicked stench"

APPENDIX C

EXPRESSING POSITIVE SENTIMENT

S/N	adverb	Sense		
1	beautifully	r.01	in a beautiful manner	Her face was beautifully made up
			Beautiful (a1) – delighting the senses or exciting intellectual or emotional admiration	A beautiful child
			Beautiful (a2) of weather-highly enjoyable	what a beautiful day
2	happily	r.02	in an unexpectedly lucky way	happily he was not injured
3	safely	r.01	with safety; in a safe manner	we are safely out of there
			safe a1) - (free from danger or the risk of harm	a safe trip"; "you will be safe here"; "a safe place"; "a safe bet
4	sensibly	r.01	with good sense or in a reasonable or intelligent manner	he acted sensibly in the crisis

APPENDIX D

Reporting Positive Sentiment

S/N	adverb	Sense		
1	brilliantly	r.02	in an extremely intelligent way	he solved the problem brilliantly
2	cunningly	r.01	in an attractive manner	how cunningly the olive-green dress with its underskirt of rose-brocade fitted her perfect figure
3	happily	r.01	in a joyous manner	they shouted happily
4	lovingly	r.01	with fondness; with love	she spoke to her children fondly
			love (n1) - (a strong positive emotion of regard and affection)	his love for his work"; "children need a lot of love
5	obediently	r.01	in an obedient manner	obediently she slipped off her right shoe and stocking
			Obedient (a1) - (dutifully complying with the commands or instructions of those in authority)	an obedient soldier
6	patiently	r.01	with patience; in a patient manner	he patiently played with the child
			Patient (a1) - (enduring trying	a patient smile

		circumstances with even temper or characterized by such endurance)	
7 peacefully	r.01	in a peaceful manner	the hen settled herself on the nest most peacefully
		Peace (n1) - (the state prevailing during the absence of war	
		(n2) - (harmonious relations; freedom from disputes	the roommates lived in peace together
		(n3) - (the absence of mental stress or anxiety	
8 positively	r.02	so as to be positive; in a positive manner	she intended her remarks to be interpreted positively
9 shrewdly	r.01	in a shrewd manner	he invested his fortune astutely"; "he was acutely insightful"
		shrewd (a1) - (marked by practical hardheaded intelligence	a smart businessman"; he was too shrewd to go along with them on a road that could lead only to their overthrow

	(a2) - (acting with a specific goal	the most calculating and selfish men in the community
10 successfully r.01	with success; in a successful manner	she performed the surgery successfully
	success (n1) - (an event that accomplishes its intended purpose)	
	(n2) - (an attainment that is successful)	his success in the marathon was unexpected"; "his new play was a great success
	(n3) - (a state of prosperity or fame)	"he is enjoying great success"; "he does not consider wealth synonymous with success"
	(n4) - (a person with a record of successes)	"his son would never be the achiever that his father was"; "only winners need apply"; "if you want to be a success you have

	(a2) - (acting with a specific goal	the most calculating and selfish men in the community
10 successfully r.01	with success; in a successful manner	she performed the surgery successfully
	success (n1) - (an event that accomplishes its intended purpose)	
	(n2) - (an attainment that is successful)	his success in the marathon was unexpected"; "his new play was a great success
	(n3) - (a state of prosperity or fame)	"he is enjoying great success"; "he does not consider wealth synonymous with success"
	(n4) - (a person with a record of successes)	"his son would never be the achiever that his father was"; "only winners need apply"; "if you want to be a success you have

APPENDIX E: List of Adverbs

1	absolutely	61	generously	121	rapidly
2	accidentally	62	gently	122	rarely
3	angrily	63	gladly	123	really
4	anxiously	64	gracefully	124	recklessly
5	arguably	65	graciously	125	regularly
6	awkwardly	66	greedily	126	reluctantly
7	badly	67	happily	127	repeatedly
8	beautifully	68	hard	128	restfully
9	blindly	69	harshly	129	rightfully
10	boldly	70	hastily	130	roughly
11	bravely	71	hatefully	131	rudely
12	brazenly	72	healthily	132	sadly
13	brightly	73	honestly	133	safely
14	brilliantly	74	horribly	134	sarcastically
15	busily	75	humbly	135	selfishly
16	calmly	76	hungrily	136	sensibly
17	carefully	77	hurriedly	137	seriously
18	carelessly	78	idiotically	138	shamefully
19	cautiously	79	impatiently	139	sharply

20	cheerfully	80	inadequately	140	shockingly
21	clearly	81	incredibly	141	shrewdly
22	closely	82	ingeniously	142	shyly
23	correctly	83	innocently	143	silently
24	courageously	84	inquisitively	144	sleepily
25	covetously	85	insolently	145	slowly
26	cruelly	86	ironically	146	sluggishly
27	cunningly	87	irritably	147	smoothly
28	daringly	88	jealously	148	so
29	deceitfully	89	joyously	149	softly
30	decidedly	90	justly	150	solemnly
31	deeply	91	kindly	151	speedily
32	deliberately	92	lazily	152	stealthily
33	destructively	93	loosely	153	sternly
34	devilishly	94	loudly	154	straight

35	diabolically	95	lovingly	155	stupidly
36	disgracefully	96	madly	156	successfully
37	doubtfully	97	metaphorically	157	suddenly
38	eagerly	98	mortally	158	suspiciously
39	easily	99	mysteriously	159	swiftly
40	elegantly	100	naughtily	160	tenderly
41	enormously	101	neatly	161	tensely
42	enthusiastically	102	negatively	162	terminally
43	equally	103	nervously	163	terribly
44	erroneously	104	noisily	164	thoughtfully
45	eventually	105	obediently	165	tightly
46	exactly	106	obviously	166	truthfully
47	explosively	107	openly	167	understandably
48	extremely	108	painfully	168	unexpectedly
49	faithfully	109	patiently	169	victoriously

Appendix F: List of Oxymorons

1	A just war	79	awfully nice	157	Melancholy merriment
2	A little big	80	Awfully pretty	158	Militant pacifist
3	a little pregnant	81	Beautifully ugly	159	Minor crisis
4	A new classic	82	Beggarly riches	160	Minor miracle
5	Absent presence	83	Big baby	161	Negative growth
6	absolutely unsure	84	Bitter sweet	162	Negative income
7	abundant poverty	85	Blind sight	163	New antique
8	academic fraternity	86	Brisk vacancy	164	No choice
9	Academic sorority	87	Cheerful pessimist	165	Objective opinion
10	Accidentally on Purpose	88	Civil war	166	Old news
11	accurate estimate	89	Clearly confused	167	One-man band
12	accurate horoscope	90	Clearly misunderstood	168	Only Choice
13	accurate rumours	91	Clever foolishness	169	Open secret
14	accurate stereotype	92	Comfortable misery	170	Openly closed
15	acrophobic mountain climber	93	Conspicuous absence	171	Openly deceptive
16	Act naturally	94	Constant variable	172	Ordered chaos
17	active retirement	95	Cool passion	173	Ordered disorder
18	actual re-enactment	96	Crash landing	174	Original copy
19	acute apathy	97	Cruel kindness	175	Overbearingly modest
20	acute dullness	98	Dark light	176	Paid volunteers

21	adult children	99	Darkness visible	177	Painfully beautiful
22	Adult male	100	Deafening silence	178	Paper tablecloth
23	advanced BASIC	101	Deceptively honest	179	Paper towel
24	advanced beginner	102	Deeply superficial	180	Passive aggressive
25	Advantageous disadvantage	103	Definite possibility	181	Peaceful conquest
26	Affirmative action	104	Definitely maybe	182	Peaceful war
27	affordable housing	105	Deliberate speed	183	Plastic glasses
28	aging yuppie	106	Devout atheist	184	Plastic silverware
29	agree to disagree	107	Disgustingly delicious	185	Poor health
30	Airline Food	108	Dull roar	186	Positively negative
31	airline schedules	109	Eloquent silence	187	Pretty ugly
32	all alone	110	Endless hour	188	Properly ridiculous
33	All natural artificial flavour	111	Even odds	189	Public secret
34	altogether separate	112	Exact estimate	190	Random order
35	almost candid	113	Extent life	191	Recorded live
36	Almost done	114	Faithfully unfaithful	192	Regularly irregular
37	almost exactly	115	Falsely true	193	Resident alien
38	almost pregnant	116	Farewell reception	194	Restrictive freedom
39	Almost Ready	117	False tranquillity	195	Run slowly
40	almost safe	118	Fine mess	196	Sad smile
41	almost suddenly	119	Foolish wisdom	197	Same difference
42	almost surprised	120	Found missing	198	Scalding coolness
43	almost totally	121	Free love	199	Seriously funny

44	alone in a crowd	122	Free prisoner	200	Shrewd dumbness
45	Alone together	123	Freezer burn	201	Silent scream
46	amateur expert	124	Friendly fire	202	Simple complication
47	Amazingly awful	125	Friendly hostility	203	Small crowd
48	American culture	126	Friendly takeover	204	Soft rock
49	American education	127	Genuine imitation	205	Sophisticated naïveté
50	American English	128	Good grief	206	Stand down
51	amicable divorce	129	Growing smaller	207	Static flow
52	among the first	130	Guest host	208	Steel wool
53	Amtrak schedule	131	Heavy diet	209	Strangely familiar
54	Anarchy Rules!	132	Historical present	210	Student teacher
55	anonymous colleague	133	Honest lie	211	Sweet sorrow
56	Anti-Missile Missile	134	Honest thief	212	Terribly good
57	anticipated serendipity	135	Humane slaughter	213	Terribly pleased
58	anticipating the unanticipated	136	Icy hot	214	The sound of silence
59	anxious patient	137	Idiot savant	215	Theoretical experience
60	apathetic interest	138	Ill health	216	Tragic comedy
61	apathetically urged	139	Impossible solution	217	Transparent night
62	Apple tech support	140	Intense apathy	218	True fiction
63	approximate solution	141	Joyful sadness	219	True lies
64	approximately equal	142	Jumbo shrimp	220	True myth
65	arms limitation	143	Larger half	221	Typically weird
66	army intelligence	144	Lascivious grace	222	Unbiased opinion

67	arrogant humility	14 5	Lead balloon	22 3	Unconscious awareness
68	Artificial Grass	14 6	Least favourite	22 4	Unpopular celebrity
69	artificial intelligence	14 7	Liquid gas	22 5	Upward fall
70	assistant supervisor	14 8	Liquid marble	22 6	Virtual reality
71	astronomically small	14 9	Living dead	22 7	Walking dead
72	athletic scholarship	15 0	Living end	22 8	Weirdly normal
73	authentic replica	15 1	Living sacrifices	22 9	Wireless cable
74	authentic reproduction	15 2	Loosely sealed	23 0	Wise fool
75	authoritarian anarchy	15 3	Loud whisper	23 1	Working holiday
76	Auto Pilot	15 4	Love hate	23 2	Working vacation
77	Awfully good	15 5	Loyal opposition	23 3	Zero tolerance
78	Awfully lucky	15 6	Magic realism		