GOTTFRIED WILHELM LEIBNIZ UNIVERSITÄT HANNOVER

MASTER THESIS

Mining Opinionated Product Features From Amazon Reviews

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Abstract

People's opinions are important piece of information for making informed decisions. Today because of Internet availability the Web has become an excellent source of consumer opinions. However, due to the fact that amount of opinionated text is growing rapidly, it is getting impractical for users to read all reviews to make a good decision. Reading different and possibly even contradictory opinions written by different reviewers even make them puzzled. Since, opinionated text is growing rapidly as a result, it is getting difficult to monitor consumer opinions for the manufactures and providers. These needs have exhilarated a new way of research on opinion mining product feature extraction. In opinion mining feature extraction is important task, since the customers do not normally express their product opinions completely according to individual features.

The main subject of this master thesis is to investigate different steps (product feature extraction, product feature sentiment and dependency-based extracting opinionated phrases) to automated analysis, extraction of opinions and product features from customer reviews by using data mining and natural language processing techniques. It focuses on mining opinionated product features from customer reviews and the characteristics of customer reviews and extract features and corresponding opinion phrases of different products from Amazon Reviews.

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Finally, if I don’t mention their name, it will be incomplete, no doubted my mother, father, sister and uncle, who gave me support and inspiration to come to Germany for higher study. I am dedicating this work to them, the parts of me.

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List of Abbreviations

NLP	**N**atural **L**anguage **P**rocessing
WSF	**W**hat (it) **S**tands **F**or
NN	**N**oun singular or mass
NNS	**N**oun, plural
NNP	**P**roper noun, singular
NNPS	**P**roper noun, plural
JJ	**A**djective
JJR	**A**djective, comparative
JJS	**A**djective, superlative
RB	**A**dverb
RBR	**A**dverb, comparative
RBS	**A**dverb, superlative

Chapter 1

Introduction

1.1 Motivation

Opinion mining (also called sentiment analysis) is the computational study of subjective information towards different entities. Entities usually refer to products, organizations, services or their features, functions, components and attributes. Opinion mining is a major task of Natural Language Processing (NLP) that studies methods for identifying and extracting opinions from written text (i.e., customer reviews, forum discussions, and blogs). With the growth of social media availability on the Web, individuals and organizations are increasingly using the opinions in these media for decision making.

As people attempt to discover what other people think about something on the Web, the response is an enormous amount of data, which makes it difficult to find useful information easily. For organizations, tracking customer feedback can help to measure the level of satisfaction and make optimal manufacturing and selling decisions. Due to human mental and physical limitations, it is difficult to manually gather and analysis the massive amount of information on the Web. Therefore, a system that can automatically extract opinion is increasingly desirable. Such a system extracts relevant information and presents it in a manner that is easy to read and understand in order to make informed decisions.

To gather the initial data, most e-commerce web-pages provide a feedback or review area where individual customers can exchange their experience and opinions. The customer review content is often presented as a natural language text in an unstructured form. Since the amount of reviews is large, it is hard, if not impossible, to read all of them and to keep track of all expressed opinions on the different features of the product or service. Selecting a few reviews to read may lead to a bias, so it is clear that more advanced and automated methods for processing and mining opinion are needed for analyzing and extracting meaningful information [1].

In the past decade, opinion mining has become a popular research topic due to its wide range of applications and many challenging research problems. The topic has been studied in many fields, including natural language processing, data mining, Web mining, and information retrieval [2].

Mining opinionated product feature aims to extract major features of an item and to generate opinion of each feature from customer reviews. Features are attributes or components of items (e.g., 'costume', 'tutu', etc. can be potential features for a cloth). In this thesis, we focus on the problem of mining opinionated product features because of its key role in the area of opinion mining. The importance of this problem is not only due to easing the process of decision making for customers by providing a decomposed view of features, but also due to the ability of utilizing the extracted features in other opinion mining systems, e.g., opinion generation, opinion question answering, etc. In our work, we present a comprehensive review of the state-of-the-art methods according to the following categorization: product feature extraction; product feature sentiment and dependency-based extracting opinionated phrases.

The main objective of this thesis is to specifically analyze customers' opinionated reviews, identify and extract features and opinions and present them as feature-opinion sets. This research explores the use of natural language processing techniques and mainly focuses on analyzing and extracting opinions and features from Amazon product reviews text so called "Amazon customer reviews".

1.2 Research Problem and Objectives

1.2.1 Research Problem

Mining opinionated product features from customer reviews aims to analytically identify product features and their corresponding opinions from a collection of opinionated reviews. It involves two main subtasks:

- Product feature identification: Given a specific product or service review (e.g. cloth, video game or baby-product), the aim is to automatically extract all possible and relevant product features from reviews. For example, from "costume is good," and "game was exciting," extract the word "costume" and the word "game" which present in cloth's and video game's feature. Having extracted the relevant features leads us to develop methods to detect a product's features allows us to develop new methods of detecting product features and their associated opinions from reviews.
- Sentiment expression identification: Researchers in sentiment analysis have focused mainly on two problems: detecting whether the text is subjective or objective, and determining whether the subjective text is positive or negative. Our second task is to identify the corresponding opinions for each extracted feature. In the previous example, the system detects sentiments, the word "good" and the word "exciting", then analyses the polarity to be negative or positive.

  Given a set of reviews:

$$D = \{d_1, d_2......d_n\}$$

This review set referring to an entity, e.g product, category, service, topic, issue etc. Our goal is to find:
1) product features from the review set; 2) sentiment of these features.

1.2.2 Research Objectives

The objective of this study is to improve the effectiveness of mining opinionated product features , which can be achieved by developing a technique to identify, extract, analyze and then select useful information. The main objectives of this research are:

- identify and extract all possible features from reviews using Natural Language Processing (NLP) techniques;

- perform sentiment analysis on the extracted features;
- construct an effective approach to group and select features and opinion phrases using data mining techniques and natural language processing techniques.

1.3 Implication of the Study

Mining opinionated product features from Amazon Reviews is a challenging problem for feature extraction, opinion mining and sentiment analysis. This research contributes to novel methods to identify and extract product features and sentiment from customer reviews by employing natural language processing (NLP) techniques. This is performed through data mining, machine learning, linguistics and statistical techniques, Association Rule Mining, in which it produced a set of rules based on NLP techniques and sentiment analysis and opinion phrases extraction from reviews.

1.4 Outline of the Research Work

This thesis consists of seven chapters. Chapter 1 describes our motivation, the research problem and significance study. Chapter 2 discusses the background and basic concept, then Chapter 3 discusses the related work. Chapter 4 discusses the overall idea of our approach namely feature and opinion extraction using Association Rules and SentiWordNet as well as dependency based approach where we used Stanford CoreNLP for extracting opinion phrases. Chapter 5 discusses the experimental findings with evaluation has been explained. Chapter 6 concludes this research and recommends possible directions for future work and open issues. Finally, Chapter 7 discusses the implementation details.

Chapter 2

Background and Basic Concept

2.1 Definitions

Product Feature Extraction focused on determining features from the reviews and identifying opinions on the reviews not considering important feature of the reviews [22]. Feature are generally nouns or noun phrases, which typically appear as the subject object of the review sentence (i.e., costume, price, quality etc).

Opinion mining is the field of study that analyzes people's opinions, sentiments, evaluations, attitudes, and emotions from written language [3]. It has attracted a lot of researchers from different areas of research including natural language processing, data mining, machine learning, linguistics, and even social science.

The term "opinion mining" was firstly presented in [4], where the author proposed some techniques for opinion mining and classified opinions as positive or negative. An opinion is an individual's private state; it exemplifies the individual's assessments, evaluations, beliefs, judgments and ideas regarding a particular item/subject/topic. Opinions of others can have great impact on and offer guidance for governments, social communities, individuals and organizations in the process of decision-making by [5]. When considering other people's opinions, human beings need concise, accurate and timely information so they may make correct and quick decisions. Opinions make human beings capable of integrating the different experiences, approaches, knowledge and wisdom of several people when making decisions.

2.2 Necessitates for Opinion Mining

Today online opinions have turned into a kind of virtual currency for businesses looking to market their products, identify new opportunities and manage their reputations.[1]

Many businesses are now employing opinion mining techniques to track customer feedbacks to act appropriately. Recently one of Canada's largest Internet marketing companies reported some statistics on the review revolution. [2]

- 92 percent of online consumers have more confidence in information found online than they do in anything from a salesclerk or other source.
- 70 percent consult reviews or ratings before purchasing.
- 97 percent who made a purchase based on an online review, found the review to be accurate.

[1]Wikipedia. Sentiment analysis.
[2] http://www.searchenginepeople.com/blog/12-statistics-on-consumer-reviews. htmlixzz2DkFWhnBg

- 34 percent have turned to social media to share their feelings about a company. 26 percent to express dissatisfaction, 23 percent to share companies or products they like.

Pang et al. [23] also report the results of two surveys on American adults which show strong demand for opinions. The authors summarize the surveys' findings as follows:

- 70 percent consult reviews or ratings before purchasing.
- 81 percent of Internet users have done online research on a product at least once.
- 20 percent do online research every day.
- Between 73 percent and 87 percent report that reviews had a significant influence on their purchases.
- 30 percent posted an online comment or review regarding a product or service.

The authors not only disclose users "need" for online opinions, but also report that 58 percent of people indicate that online information was missing, impossible to find, confusing, and/or overwhelming. Opinion mining is not only very useful for consumers to know the opinions of other users before they use a service or purchase a product, but also crucial for businesses to understand consumer opinions on their products and services [24].

2.3 Opinion Mining Terminologies

In this section we define the basic terminologies currently used in the area of opinion mining.

Fact :A fact is something that has occurred or is correct. [3]

Opinion: : An opinion is a belief about matters commonly considered to be subjective, and is the result of emotion or interpretation of facts. [4]

Subjective/Opinionated Text: A text is subjective or opinionated if it expresses personal feelings or beliefs, e.g. opinions.

Objective Text: An objective text expresses some factual information about the world.

Item: An item is a concrete or abstract object such as product, service, person, event, organization [3]. An item can be represented as a hierarchy of components, sub-components, etc.

Review: A review is a subjective text containing a sequence of words describing opinions of reviewer regarding a specific item. Review text may contain complete sentences, short comments, or both (Figure 2.1).

- Short comments or Pros/Cons: The reviewer can describe Pros and Cons of the item separately. Short comments contain sentence segments that are usually separated by comas, e.g., "great cotton quality, poor manufacturing quality, affordable price".

[3]Wikipedia. Fact. https://en.wikipedia.org/wiki/Fact
[4]Wikipedia. Opinion. http://en.wikipedia.org/wiki/Opinion

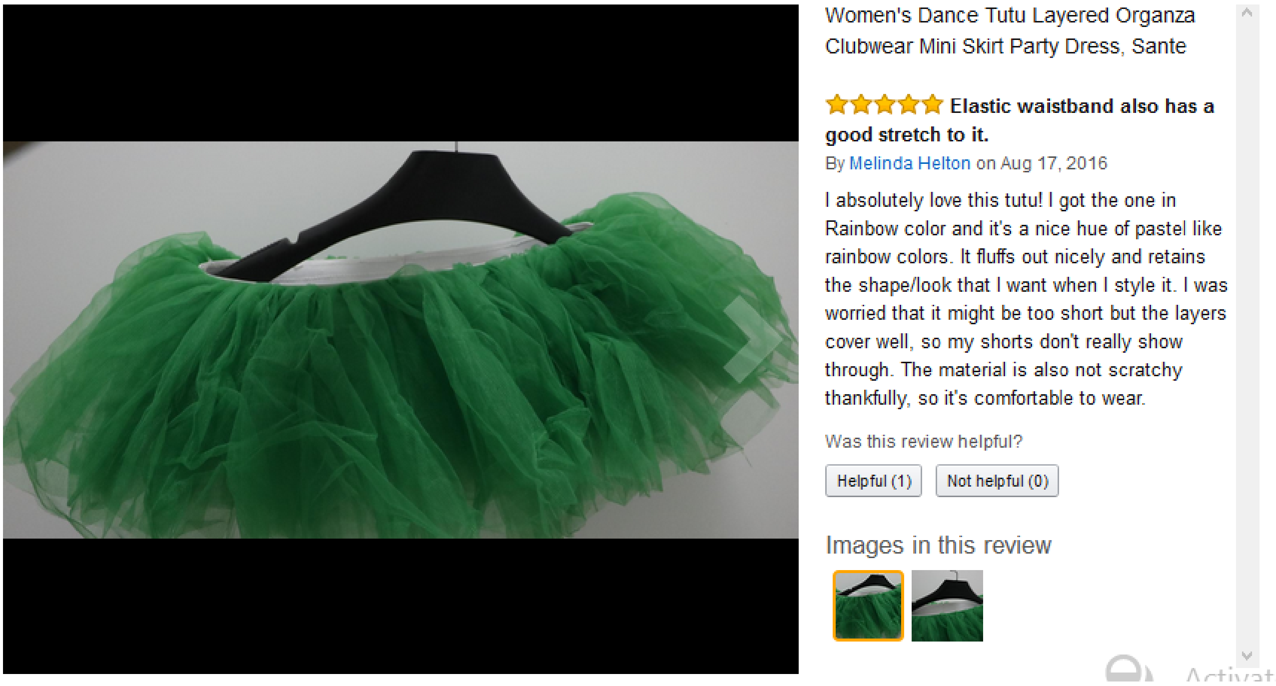

FIGURE 2.1: A sample review from Amazon.com

- Full text review or free format: The reviewer can write freely, i.e., no separation of Pros and Cons. Full text reviews contain complete sentences and tend to be long. Figure 2.1 is a full text review. The sentences are usually complex and have a large amount of irrelevant information, e.g., "When I bought it I was not quite sure it is the best choice, but now I am pretty sure it is the best video game with hidden objects finder and great fun for adults too".

Feature: A feature is an attribute or component of the item that has been commented on in a review. If an feature appears in a review, it is called explicit feature; otherwise it is called implicit [12]. Current works mainly focus on extracting explicit features and only a few simple methods are proposed for identifying implicit features.

- Explicit Features: Features that are explicitly mentioned as nouns or noun phrases in a sentence, e.g., 'poor quality' in the sentence "These were a good buy - great color and quality for the price".

- Implicit Features: Features that are not explicitly mentioned in a sentence but are implied, e.g., 'price' in the sentence "Video Game is so expensive.", or 'quality' in the sentence " Trouser is very small size and very transparent fabric".

Opinion Orientation: A sentiment can be classified in n-level orientation scale. Sentiment orientation is an intended interpretation of the user satisfaction in terms of numerical values.

- Polarity: Polarity is a two-level orientation scale. In this scale a sentiment is either positive or negative.

- Rating: Most of the reviewing websites use five-level orientations, presented by stars in the range from 1 to 5 which is called rating.

TABLE 2.1: Part of the Penn Treebank part-of-speech tags.

Tag	Description	Example
DT	Determiner	these
JJ	Adjective	bad
NN	Noun, singular or mass	game
CC	Coordinating Conjunction	and
RB	Adverb	very
VB	Verb, base form	recommend

Part-of-Speech (POS) Tag: The part-of-speech of a word is a linguistic category that is defined by its syntactic or morphological behavior. Common POS categories in English grammar are: noun, verb, adjective, adverb, pronoun, preposition, conjunction, and interjection. POS tagging is the task of labeling (or tagging) each word in a sentence with its appropriate part of speech. Most of the opinion mining works use the standard Penn Treebank POS Tags.Table 2.1 shows some of the common POS tags.

2.4 Sentiment Analysis and Opinion Mining

Sentiments may be narrated as opinions, ideas or as judgments manifested by emotions [6]. As [7] stated, "One of the challenges related to sentiment analysis is identifying the objects of the study of opinions and subjectivity. Originally, subjectivity was identified by the prominent linguist R. Quirk [8]". Quirk defines private state as something that is not open to objective observation or verification [7]. These private states include emotions, opinions and speculations. Computational linguistics mainly focuses on opinions rather than on sentiments, feelings or emotions. The terms 'sentiment' and 'opinion' are often used interchangeably in the literature.

Human sentiment knowledge grows through day-to-day cognitive interactions. Sentiment is not a direct property of languages. An intelligent system should need some prior knowledge to act properly. Sentiment knowledge is generally wrapped into computational lexicon, technically called sentiment lexicon, e.g SentiWordNet.

Information on the Web that is preserved in text documents can be divided into two categories: factual and opinionated information. Usually, facts relate to objective articulations about aspects, events, and their attributes. According to [9], opinions are usually subjective manifestations that outline people's sentiments, appraisals, or feelings toward the aspects, events, and their properties. On the other hand, demonstrate opinion [10] in the context of four terms: Topic, Holder, Claim, and Sentiment. The Holder believes a Claim about a topic that is usually associated with a Sentiment, such as "good" or "poor". Kim and Hovy [10] draft a sentiment as an explicit or implicit articulation in text indicating the Holder's positive, negative, or neutral expression toward the Claim about the Topic, and the sentiments always involve the Holder's emotions and desires.

Various Machine Learning and Data Mining algorithms can be used for sentiment analysis tasks. For example "The quality of this trouser is good". In this task, opinion holder is the user who has given the review. Opinion object is the "quality" of the trouser and the opinion word is "good", which is positive in its orientation. The main objective of sentiment analysis is polarity classification. Semantic orientation determines whether a sentence has positive, neutral or negative orientation. Machine Learning system is a system which learns from observations, training, experiences etc. Supervised learning generates a function that maps inputs to desired outputs also known as labels as they are training examples labeled by human experts[13]. Any supervised learning method can be used e.g., Naïve Bayes classification, and support vector machines.

The sentiment analysis can be performed at one of the three levels: the document , sentence or feature level [14].

- Document Level Sentiment Classification: In document level sentiment analysis the main challenge is to extract informative text for inferring sentiment of the whole document.
- Sentence Level Sentiment Classification: The sentiment classification is a fine grained level than document level sentiment classification in which polarity of the sentence can be learned.
- Feature Level Sentiment Classification: Product features are defined as product attributes or components. Analysis of such features for identifying sentiment of the feature is called as feature based sentiment analysis. In this approach, positive or negative opinion is identified from the already extracted features. It is a fine grained analysis model comparing to the other models.

Opinion mining, also known as sentiment analysis, is one of the most explored areas in computer science in the last few decades. Although a formidable amount of research has been done, the reported solutions and available systems do not yet satisfy the requirements of the end user. The main issue is the various conceptual rules that govern sentiment. There are many different clues (possibly unlimited) that can convert these concepts from realization to verbalization of a human being.

Human psychology directly relates to the paradigms of social psychology, culture, pragmatics and governs our sentiment realization. Proper incorporation of human psychology into computational sentiment knowledge representation appears to be a step in the right direction.

Sentiment analysis is also termed as subjectivity analysis or opinion mining dealing with the computational presentation of opinion, sentiment, and subjectivity in text involving Natural Language Processing (NLP), text analysis, and computational linguistics [11]. It aims at comprehending the expression or opinion from a speaker or writer with respect to a certain topic. The expression may reflect the judgement, opinion, or evaluation of the writer and indicate her affective state at the time of writing. The affective state means how the writer was feeling at that time or the emotional communication intended to affect the reader of the text.

Chapter 3

Related Work

In this section we discuss some of the related work that has been done on finding features in customer reviews. We investigate three existing classification techniques which are representative for their classes: feature, sentiment and opinion classification.

3.1 Product Feature Extraction

One of the most well known methods to find explicit features is proposed by Hu and Liu in [25]. This method first extracts the features that are frequently mentioned in the review corpus. Since it is assumed here that explicit features are most likely to be nouns or noun phrases, these are extracted from all sentences and are included in a transaction file. In order to find features that people are most interested in, Association Rule Mining [26] is used to find all frequent item sets. In this context, an item set is a set of words or phrases that occur together. When the final list of frequent features is known, the method extracts all opinion words that are nearby the frequent features. To that end, it exploits the fact that opinion words are most likely to be adjectives. The found opinion words are used to find infrequent features, based on the idea that people often use the same opinion words for both frequent and infrequent features. If a sentence does not contain a frequent feature but does contain one or more opinion words, the proposed method extracts the noun nearest to that opinion word and this noun is stored in the feature so called infrequent feature. A disadvantage of this method is that nouns or noun phrases that are more used in general will also be annotated as feature, favoring false positives. In the next paragraph we present a method which alleviates this issue.

B.Liu [27] proposed set of techniques opinions expressed in customer reviews and qualitative and quantitative analysis of that opinions. For example document level opinion mining identifies the overall sentiment expressed an entity (e.g., cellphone) in a review document but it does not associate opinions with specific aspects(e.g., picture quality, screen).

Yu et al. proposed an aspect ranking algorithm based on the probabilistic regression model to identify important product aspects from online consumer reviews [29]. However, it does not focus on extracting features commented on explicitly in reviews, but fairly on ranking product features that are actually coarse-grained clusters of specific features.

3.2 Sentiment Classification

Pang, et. al [30] tried to examine whether it suffices to treat sentiment classification simply as a special case of topic-based categorization (with the two "topics" being positive sentiment and negative sentiment). Three standard algorithms: Naive Bayes classification, maximum entropy classification, and support vector machines are tested. It is reported that the results produced via machine learning techniques are quite good in comparison to the human-generated baselines. In terms of relative performance, Naive Bayes tends to do the worst and SVM's tend to do the best, although the differences aren't very large. However, their approach is based on the assumption that users' opinions are polarized.

The wide area of work available in the literature focuses on the automatic analysis of opinions on products [31], leaving aside opinions about enterprises and their services (e.g., hotels, travel agencies, shops, etc). Different from opinions on products (which have a limited number of well known features), opinions on services may be much more subjective, and the features being commented on are not always clearly stated in the text. This way, it is harder to automatically identify which aspect or event pleased or displeased the customer. Liu [24] also defines three mining tasks for opinionated text in his book. He further extends this categorization in his handbook [32] as follows: sentiment and subjectivity classification, feature-based opinion mining, sentiment analysis of comparative sentences, opinion search and retrieval, and opinion spam detection. In his recent book [27] he defines three general categorizations for opinion mining tasks: document-level, sentence-level, and phrase-level.

Sentiment classification assumes that the given document is opinionated and aims to find the general opinion of the author in the text [33]. For example, given a product review, it determines whether the review is positive or negative. Sentiment classification, in contrast to subjectivity analysis, does not usually need extra manual effort for annotating training data. Training data used in sentiment classification are mostly online product reviews that have already been labeled by reviewers with the assigned overall ratings (usually in the range form 1 to 5). Typically reviews with 4-5 stars are considered positive, while review with 1-2 stars are considered negative [32].

3.3 Opinion classification

Opinion tasks are mainly formulated as classification problems where the input comments or reviews should be classified into a few predefined categories. In ***subjectivity classification*** , input is classified as subjective or objective. In ***sentiment classification*** , a subjective reviews or comments are classified as positive, negative, or neutral.***Opinion helpfulness*** prediction classifies an opinion as being helpful or not helpful (sometimes more classes are defined). And, ***opinion spam*** detection classifies opinions as spam and not spam.

3.3.1 Polarity classification

Typically, the polarity classification is considered a binary classification problem. Given a subjective text (e.g., a customer review or an editorial comment), the goal is to determine whether the general tone of the text is predominantly positive or negative [35]. Obviously, a crucial point is how to define the two poles of sentiment. What is a positive opinion and what is a negative opinion? It is impossible to provide a single answer here. A definition is heavily dependent on the concrete application scenario, and differences may be subtle. For example, in the context of political debates, "positive" may refer to support and "negative" may refer to opposition. When classifying customer reviews, the definition typically considers the subjective nature of the text. Does the reviewer like or dislike the product? Providing a specific definition becomes even more important when computationally treating the sentiment polarity as a classification task.

Related contributions in this area include those by [34] and [35] who investigated different approaches for identifying the polarity of product reviews and movie reviews respectively. The opinions expressed by a writer towards a target can be divided into a number of classes such as "positive", "negative", and "neutral" (i.e. determining the valence); or into a discrete measurement scale such as "excellent", "good", "satisfactory", "poor", and "very poor"; or by a number of emotions such as "joy", "sadness", "anger", "surprise", "disgust", and "fear". In this context, a sentiment analysis process is a spectrum of tasks where each task articulates a sentiment.

3.3.2 Subjectivity classification

Subjectivity classification is primarily considered as a binary classification task. Its goal is to separate subjective from objective information. Again, the problem may be tackled at different levels of granularity. For instance, at the document level the aim is to distinguish review-like documents from non-review documents or factual newspaper articles from editorial comments. Subjectivity classification is also an important subtask in sentiment retrieval. Many supervised and unsupervised techniques have been explored for subjectivity annotation tasks by various researchers over a long period [7]. Several linguistic resources and tools like dependency parsing, named entity recognition, morphological analysers, stemmer, SentiWordNet, and WordNet have been used in the subjectivity detection task. However, in the case of morphologically rich Indian languages like Bengali, such resources and tools are not readily available. Highly inspired by [36] the present work was initiated to develop a subjectivity classifier that will work on unannotated text documents.

3.3.3 Emotion classification

The task of detecting the expression of emotion in natural language text can be considered as a refinement of the sentiment polarity classification task. The goal is to classify a piece of text according to a predefined set of basic emotions. Whereas sentiment polarity is commonly viewed as dichotomous (positive vs. negative), emotion classification tries to identify more fine-grained differences in the expression of sentiment. Most commonly, [37] six "basic" emotions - anger, disgust, fear, happiness, sadness, and surprise - are used as class labels for this task. Ekman [28] presented about basic emotions and few changes. Ekman's extended model [38] may also serve as a base. Besides deriving a categorization from psychological theories of emotion, class labels may also be defined ad hoc, based on concrete application needs.

3.4 More relevant to our work

The most relevant to our work is [25], where the author has proposed an association rule mining approach in order to identify product features, but it cannot deal with the identification of implicit features. While consider that an implicit product feature should satisfy the following two conditions: the related product feature word doesn't occur explicitly; the feature can be deduced by its surrounding opinion words in the review.Also relevant is [46], where the authors proposed an features based opinion mining system to classify the reviews as positive, neutral or negative for each feature.

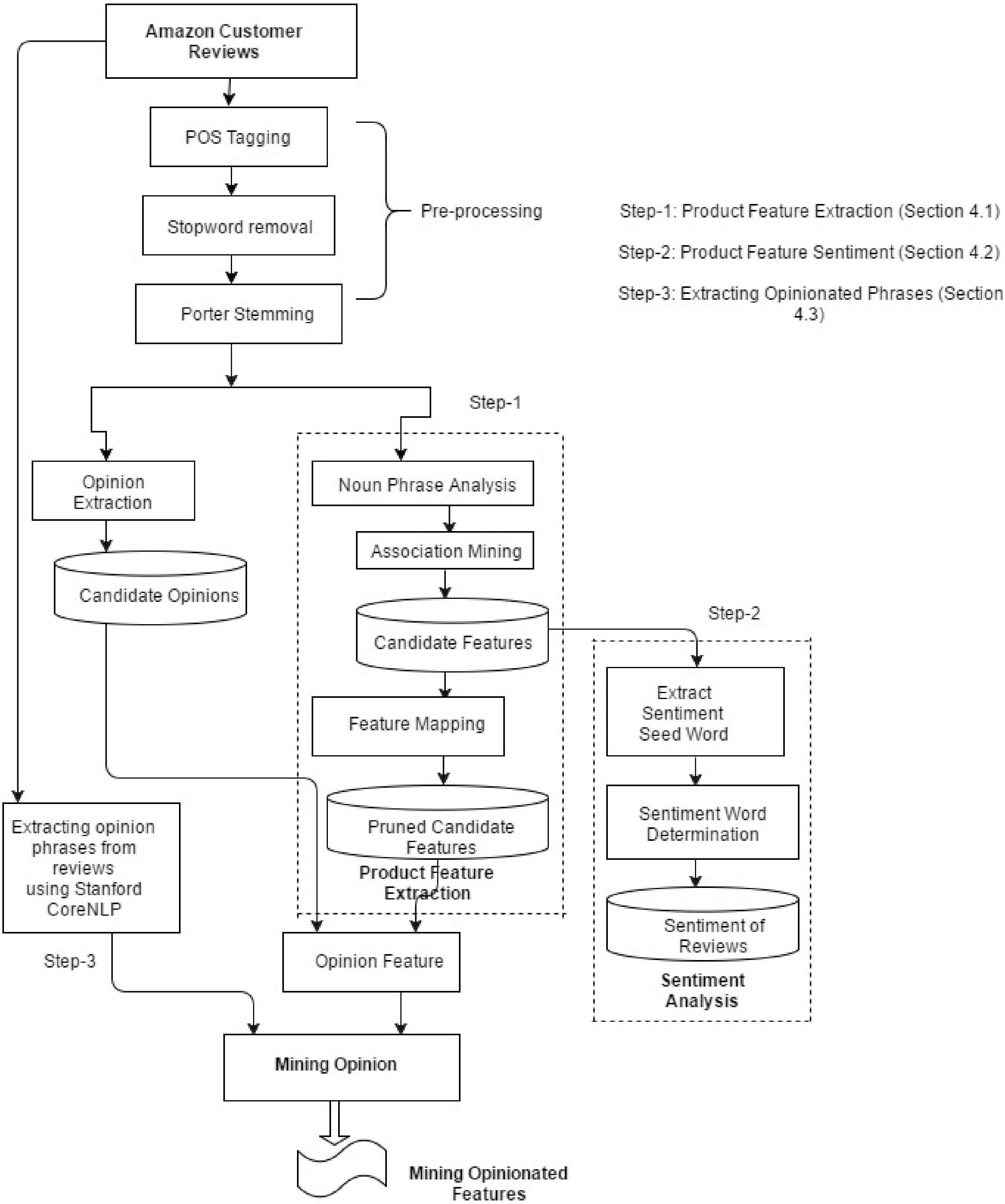

FIGURE 3.1: System Architecture.

Chapter 4

Our Approach

Figure 3.1 explain an architectural overview for our Mining Opinionated Product Feature system. The system performs the opinion mining in three main steps: 1) feature extraction; 2) sentiment analysis; and 3) opinion product feature mining. Feature extraction technique is used to extract the expression which is useful or important from the given review. Sentiment analysis attempts to determine which features of text are indicative of it's context (positive, negative or objective). Opinion feature mining revolves around finding features of products mentioned in the reviews, deploy sentiment analysis from extracted feature set, finding opinions shared in the reviews and then matching them together using topic modeling approach.

4.1 Step-1: Product feature extraction

The goal is to extract product features, main idea is to apply frequent-nouns based approach to set of constraints on high-frequency noun phrases to identify features and frequent noun sets based approach. A feature are expressed by a noun, adjective, verb or adverb. However, recent research [24] shows that 60-70 percent of the features are explicit nouns. That is why we consider noun word as feature set. In reviews people are more likely to talk about relevant feature which suggests that feature should be frequent nouns. However, not all of the frequent nouns are features. Therefore, different filtering techniques are applied on frequent nouns to filter out non-feature, we called them infrequent feature.

4.1.1 Frequent-nouns based approach

The goal of this step is to extract product features according to the noun frequency that have been commented on in the product reviews. Our purpose aims to find what people like and dislike about a given product, therefore, how to find the product features that people talk about is the crucial step based on its part of speech, word frequency, the word itself. As from the data word with certain frequency (<78) and words with certain part of speech (like Noun) and finally words themselves play a key role in identify feature. We use single Word unigram model. It uses POS (Parts Of Speech) tagging. Single words or unigram from the given reviews are extracted. We also used wsj left3words model of Stanford Tagger. The code is restricted to extract unigram or single words which are Nouns from the given set of reviews.

E.g. for product-1: Review- 1 'Perfect red tutu for the price. I bought it as part of my daughters Halloween costume and it looked great on her'.

Review-2 'Pretty good quality tutu for a great price. My daughter loves this for her tot ballet class'.

Review- 3 'My 5 year old daughter get this today for Christmas. She and we are very pleased with it'.

Review- 4 'Got this for my niece and she loved it! There is a silk lining so that it doesn't scratch the legs which is a big plus! Shipped fast too'.

E.g. for product-2: Review- 5 'Great game when it first came out, and still a great game'.

Review- 6 'Gift for my granddaughter. Likes the game a lot, but prefers to just listen to the music and sounds. We use it at my house on a separate computer (just for Lana). Money well spent-provides hours of amusement and education'.

Review- 1 and Review- 2 are describing similar opinion but in the different way here is the frequent feature is ***'tutu' and 'price'***. ***Review- 3 and Review- 4***. share different opinion describing different features: ***Review- 3*** is about ***'Christmas'*** while ***Review- 4*** isn't describing anything concrete except ***'implicit feature tutu'***. ***Review- 5*** is about ***game*** and ***Review- 6*** is ***opinion about game*** .

4.1.2 Part-Of-Speech Tagging (POS)

When extracting product features from a review it must be considered what characteristics can be used to identify them. According to Hu and Liu product features are usually nouns or noun phrases in reviews. Part-of-speech tagging must therefore be utilized to identify them. POS tagging is the process of classifying words according to their word class (noun, verb, adjective, etc). It is then possible to further classify those words into sets of words (phrases) according to predefined rules of combining words of certain classes, a process known as chunking. I performed those tasks using the Stanford Log-linear Part-Of-Speech Tagger[1]. The following shows an example of a sentence which has been part-of-speech tagged and chunked.

(S This/DT (NP tutu/NN) is/VBZ (JJP great/JJ) ,/, I/PRP (VBPP really/RB love/VBP) it/PRP)

For instance, /NN indicates a noun and NP indicates a noun phrase. For this research I expanded on Hu and Liu's methods consider only noun phrases to find features. I included other chunking patterns to try to capture opinion words that were not adjectives as well as relevant words accompanying opinion words. I created four chunking rules:

Noun Phrases (NP) – Captures simple noun phrases, includes all types of nouns directly adjacent to each other.

Adjective Phrases (JJP) – Captures adjectives and relevant words often used directly in front of adjectives to increase or decrease the significance of the adjective, known as intensifiers.

[1] Wikipedia. Fact. http://nlp.stanford.edu/software/tagger.html

This could for example be "really great", where "really" is an intensifier and "great" is the adjective the intensifier modifies.

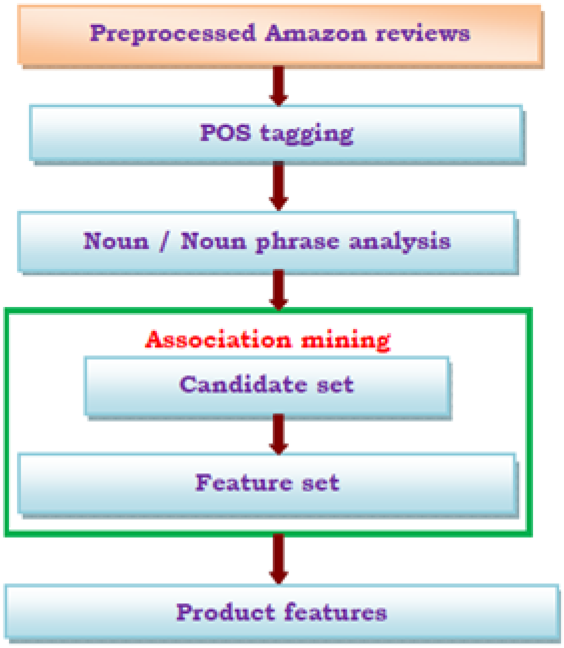

FIGURE 4.1: Product Features Extraction.

4.1.3 Method based on Association Mining

Hu and Liu et.al., [38] first presented a scheme to extract product features based on association rule mining. In Figure 4.1 shows product features extraction using association mining. The main ideas are that consumers often use the same words when they comment on the same product features, and that frequent item sets of nouns in reviews are likely to be product features, while infrequent ones are less likely to be product features. The basic steps of the algorithm are as follows:

- We find ***frequent nouns***, e.g price, costume etc. Nouns and noun phrases (or groups) are identified by a POS tagger. Only the frequent ones are kept. The reason for using this approach is that when people comment on different features of a product. Thus, frequently used nouns are usually genuine and important features.

- We find ***infrequent features*** by exploiting the relationships between features and opinion words. The first step can miss many genuine features expressions that are infrequent. This step tries to find them. The idea is that the same opinion word can be used to describe or modify different features. Opinion words that can modify frequent features can also modify infrequent features, and thus can be used to extract infrequent features. For example, "costume" has been found to be a frequent feature, and have the sentence, "The costume is absolutely amazing." If "amazing" is known to be an opinion word, then "game" can be extracted as a feature from the sentence, "The game is amazing," because the two sentences follow the same dependency pattern and "game" is also a noun.

TABLE 4.1: Manually compiled list of 10 feature indicators.

expensive, heavy, cheap, whole, soft, easily, long, slow, classic, multiple

4.1.4 Feature Mapping

When analyzing users' opinions, we note that some relevant features may not be explicitly mentioned in the text. For example, in the sentence " tutu was expensive", the word "price" was omitted, even thought the user is clearly referring to this feature. This practice makes more difficult the automatic identification of features. In this context, the adjectives and adverbs used to implicitly refer to a feature are also very important, being called feature indicators [42].

This step performs a mapping from feature indicators found in the text to the actual features being referred to. However, this mapping requires extra care, since several adjectives can be quite versatile, and their meaning is usually domain/context dependent. For example, in the sentence traffic is heavy", "heavy" does not describe the weight of the traffic.

The usual way to perform this task is via the use of a manual mapping. It is not clear yet whether there are more effective approaches, as little research has been done in the search for alternatives [43]. Our system uses a manually compiled list of 10 feature indicators for the chosen domain to identify features that are implicitly mentioned (e.g., "price") through the use of any of its indicators (e.g., "cheap" or "expensive"). Idea is to use a manually compiled list of feature phrases and check if any sentences contain single word features that implicitly appeared in the review. As several adjectives can be quite versatile therefore we generated manual mapping list with adjective and adverb phrases shown in table 4.1.

4.1.5 Pruning Candidate Feature

Not all frequent features generated by association mining are useful or are genuine features. There are also some uninteresting and redundant ones. Feature pruning aims to remove these incorrect features. This method examines features containing at least two words, called feature phrases, and removes those likely to be of no use. Hu and Liu [38] note that their association rule mining algorithm does not consider word position relative to other words. Since in natural language the order and composition of certain words are likely to be meaningful phrases this they attempted to prune meaningless phrases found by the association rule mining. They defined a feature phrase to be compact in a sentence if the word distance between any two words in a feature phrase was no greater than three and that the words were in a correct order. If a phrase is compact in at least two sentences then the feature is called a compact feature phrase. If a feature phrase is not compact in at least two sentences in their review database then the feature phrase is pruned.

4.1.6 Frequent and Infrequent Product Features Identification

Frequent features that people are most interested in. Frequent features are the "hot" features that people are most interested in for a given product. However, there are some features that only a small number of people talked about. These features can also be interesting to some potential customers so called infrequent feature. Frequent and Infrequent product features identification are shown in table 4.2.

TABLE 4.2: The effects of Association Mining on Frequent and Infrequent Product Features Identification.

Product Category	No. Of manual Features	Frequent features	Infrequent feature
Clothing	20	10	10
Video Games	20	16	04
Automotive	20	15	05
Baby	20	12	08

4.1.7 Frequent noun sets based approach

In frequent noun sets based approach, we consider multiple words on the noun sets. We used multi Word bigram model. It uses POS (Parts Of Speech) tagging. Multi words or bigrams from the given reviews are extracted. We have used wsj left3words model of Stanford Tagger, same as single word but multigram extracts binary words which are Nouns from the given set of reviews. Negative and Positive reviews are given as input to the system, it extract the required features and gives the result. Features extracted are the common nouns from the given reviews. For common nouns N is the simplified noun tag i.e.: bigrams are extracted from reviews which are the features. In order to have a big picture about the variety

FIGURE 4.2: Clothing Customer Reviews Wordcloud: Top product feature according to frequency based approach.

of Noun words on individual product categories we targeted (such as Cloth, Video Game, etc). Meanwhile, we selected most repeated words for seeking features and opinions in products, we can also recognize which terms, especially in the review text, and customers mostly used and might be considered for advertisements. By conducting the word-cloud function, we can have a basic visualization on which words are mostly used by customers.

For instance, Those customers who are interested in Clothing can be commented on its products by some Noun word such as ” costume”, ” size”, and ” price” etc. On the other hand, customers who are interested in Video Game can be commented on its products by some Noun word such as " game", " graphics", and " music" etc. In Figure 4.2, in the word cloud we can see the most frequent words used by customers for products Clothing and Figure 4.3, shows the frequent noun sets product feature.

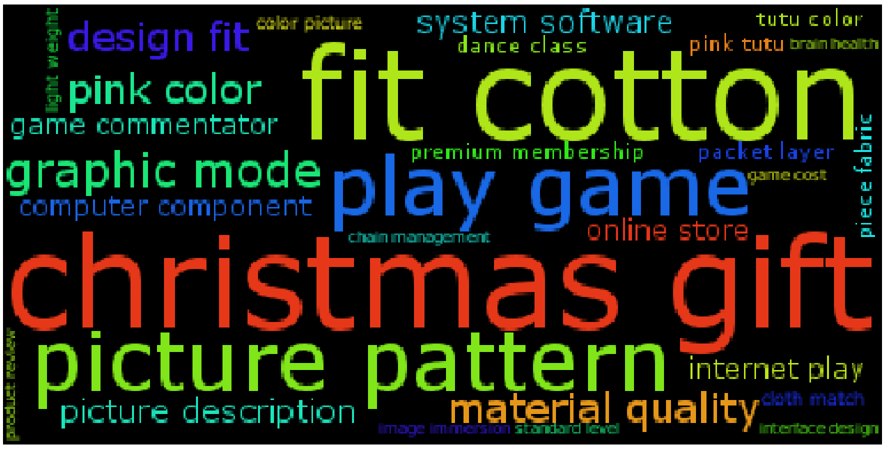

FIGURE 4.3: Clothing Customer Reviews Wordcloud: frequent noun sets product feature.

4.2 Step-2: Product feature sentiment

This approach finds the relationship between the words and sentiments to identify features. For example, the sentence "This baby product has good quality" denotes [sentiment, feature] that the feature is "quality" of this baby product and the sentiment "good" is said to be positive. This approach usually engages part-of-speech (POS) patterns to extract aspects. Liu et al. [27] has introduced an unsupervised information extraction system called OPINE which mines reviews to extract important product features. It extracts all noun phrases and keeps those with frequency greater than the threshold.

4.2.1 Sentiment lexicon-based approach

Once the part of the word that refers to the frequent and infrequent feature is found, the method for extracting the sentiment presented in [39] is used. In this method, all senses of the words are used to find the sentiment of the words, using SentiWordNet [40,41]. The sentiment found by using SentiWordNet is expressed by three scores: objectivity, negativity, and positivity. These scores range from 0 to 1, with a total sum of 1. The resulted score for a synset is the positivity score minus the negativity score. Adding up all these individual sentiment scores, after handling negations, gives the total score of the word.

For easier understanding we use two different categories of products. One data set is a collection of cloth reviews from Amazon, which we name Cloths, and the other data set is video game reviews from Amazon too, which we name Video Game. We selected top 4,875 noun words from 292 reviews of cloth product category. For product category Video Game we selected top 3,006 noun words from 228 reviews. For sentiment analysis we used SENTI WORD NET (version 3.0), a lexical resource in which each synset of WORD-NET is associated to three numerical scores Objective, Positive and Negative. The assumption that underlies the switch from terms to synsets is that different senses of the same term may have different opinion-related properties. Each of the three scores ranges from 0.0 to 1.0, and their sum is 1.0 for each synset. This means that a synset may have nonzeroscores for all the three categories, which would indicate that the corresponding terms have, in the sense indicated by the synset, each of the three opinion-related properties only to a certain degree. The attitudes towards big data were classified as "positive", "objective" and "negative". The positive and negative grades were aggregated for all terms associated with big data. In Figure 7 and 8 it can be seen that sentiments are far more positive (719) than negative (559) for Video Game and more positive (1131) than negative (802) for Cloths.

4.2.2 POS Analyzer

Parts-Of-Speech (POS) tags to every words based on the context in which they appear. The POS information is used to locate different types of information of interest inside text documents. For example, generally noun phrases correspond to product features, adjectives represent opinions, and adverbs are used as modifiers to represent the degree of expressiveness of opinions. Since, it is observed that opinion words and product features are not independent of each other rather; each sentence is also converted into dependency tree using the parser. The dependency tree, also known as word-word relationship, encodes the grammatical relations between every pair of words.

Opinionated feature extractor is responsible to extract feasible information components from review which is analyzed further to identify product features and opinions. It takes the input from Part-Of-Speech Tagger (POS Tagger) and output feasible information components after analyzing noun phrases and the associated adjectives possibly preceded with adverbs. On observation, we found that product features are generally noun phrases and opinions are either only adjectives or adjectives preceded by adverbs. Therefore, we have defined information component as a triplet <F, M, O> where, F is a noun phrase, O is adjective possibly representing product feature and M is adverb that acts as modifier to represent the degree of expressiveness of O. M is also used to capture negative opinions explicitly expressed in reviews.

The information component extraction mechanism is implemented as a rule-based system which analyzes dependency tree to extract information components. Though a large number of commonly occurring noun and adjective phrases are eliminated due to the design of the information component itself, it is found that further processing is necessary to consolidate the final list of information components and thereby the product features and opinions. During the consolidation process, we take care of two things. In the first stage, since product features are the key noun phrases on which opinions are applied, so a feasible collection of product features is identified using term frequency (tf) and inverse document frequency

TABLE 4.3: A fragmentary part of features and opinions extractor for Cloths and Video Games.

Product	Extracted Features	Opinionated Modifier
Cloth	Costume	(great(2), soft, very good (3))
Cloth	Quality	(not good(2), great, very poor(2), not bad (3), high (2))
Cloth	Price	(painful, cheap, excellent(3), very good (3), great, very high(2))
Video Game	Game	(great (2), good, excellent)
Video Game	Graphics	(not good (3), amazing, great, awesome(2), magnificent)
Video Game	Music	(modern, cool, loud, ambient, good(2))

(idf). In the second stage of analysis, however, for each product feature the list of all opinions and modifiers is compiled that are used later for polarity determination of the opinion sentences. A partial list of product features, counting number of opinions, and modifiers extracted from a corpus of 292 customer reviews on cloths and 2228 customer reviews on video game is shown in table 4.3.

4.3 Step-3: Dependency-based approach (Extracting opinionated phrases)

In this approach, several models are created for opinion extraction so that it can be applied to domain independent data sets. Most commonly used mathematical model based on supervised learning techniques are Hidden Markov Model (HMM) and Conditional Random Field (CRF), and based on unsupervised topic modeling techniques are Probabilistic Latent Semantic Indexing (PLSI) and Latent Dirichlet Allocation (LDA) [23]. We use Stanford CoreNLP tool to extract opinion phrases in our case.

4.3.1 Opinion-feature extraction from reviews

Opinion-feature aggregations and short review summaries are used to group and condense what other users think about the product in order to personalize the content served to a new user and shorten the time he needs to make a buying decision.It is becoming increasingly difficult to handle the large number of opinions posted on review platforms and at the same time offer this information in a useful way to each user so he or she can make a decision fast whether to buy the product or not. An opinion-feature is defined as a pair (feature, sentiment) like trouser nice or house clean. This is the stuff that people are generally interested in when reading a review, these key points that sum up a user's experience with the product. A very simple way to extract these pairs is to look for nouns and then pick the nearest adjective around it.

Our main goal is to extract opinion words from a large reviews corpus. We experimented on the Amazon Reviews dataset.In order to end-up with opinion words. First, basic patterns are extracted then combined in a tree-like manner to obtain more valuable opinion phrases. (N indicates a noun, A an adjective, V a verb, h a head term, m a modifier, and < h, m > an opinion phrase).

(e.g. amod(N, A) -> < N, A > I bought a tutu last summer which was great fit-> (fit, great)).

Chapter 5

Experiments

5.1 Datasets

We have conducted experiments on the customer reviews of four different product categories: Clothing , Video Games, Baby Product, and Automotive. We collected the reviews from Amazon product data [44][45] [1]. Products in these sites have a large number of reviews.The particular data used for this research was a part of more than 46 million Amazon review dataset spanning May 1996 - July 2015. Each of the reviews includes a text review, ASIN is the ID of the product and a title. Additional information available but not used in this research, include date, time, author name and location (for Amazon reviews), and ratings. Table 5.1 shows the chosen products along with the number of reviews.

5.1.1 Pre-processing

To start the pre-processing, reviews are collected from Amazon review pages. The data is in JSON format which contains different attributes. The dataset is unstructured; it may contain repetitive words, large number of words that are not at all needed in summarizing of opinions. In the pre-processing process starts with a set of customer reviews as the input from Amazon review set. Pre-processing steps (Figure 5.1) including tokenization, stop words removal such as 'and', 'or', 'that' etc. followed by porter stemming which involves simplifying target words to base words by removal of suffixes such as – ed, ate, ion, ional, ment, ator, ssess, es, ance or conversion from ator to ate etc. For example, "replacement" is stemmed to replac; "troubled" to trouble ; "happy" to happi ; "operator" to operate. The raw data is preprocessed to improve quality and word stemming are first applied to the review sentences in order to reduce the noisy information in the remaining processes. In this we work extract explicit features at the sentence level and we categorized infrequent features also. In terms of the data set, we have big JSON files where the structure of the data set is as follows:

accident

- reviewerID -> ID of the reviewer, e.g. A2SUAM1J3GNN3B,
- asin -> ID of the product, e.g. 0000013714,
- reviewerName -> name of the reviewer,
- helpful -> helpfulness rating of the review, e.g. 2/3,

[1] http://jmcauley.ucsd.edu/data/amazon/links.html

- overall -> rating of the product, and
- reviewText -> text of the review.

FIGURE 5.1: Pre-processing steps of feature extraction process.

5.2 Annotated Opinion Feature Mining Dataset

From four products categories we collected the first 50 reviews and manually read all the reviews and produced two feature lists (20 features for clothing and 20 features for video games) for each sentence in each review described in the Table 5.5 and Table 5.6. We also included a manual sentiment estimate for each opinion of a feature and characters indicating if the feature was explicitly used in the sentence or if it was referenced or other wise implied (i.e. "it was great"). This annotated review set was made available and was used in this research to test the opinion feature mining part of the research (include in the appendix).

5.3 Experimental Set-up and Results

After cleaning data the methods are evaluated for performance. The evaluation of methods pertaining to mining opinionated product feature and sentiment analysis are described below.

To find the best performing technique for mining opinionated product features experiments were conducted on the dataset described in Table 5.2. The four products categories reviewed were Clothing , Video Games, Baby Product, and Automotive. First every category of product review was part-of-speech (POS) tagged. After that the pruning methods were applied and all combinations of the mapping rules described in section 4.1.4 were executed to see what combination of product feature produced the best results.

TABLE 5.1: Confusion Matrix.

		Actual Value	
	Classes	Positive	Negative
	Positive	TP	FP
Result	Negative	TN	FN

5.3.1 Feature-based opinion mining using association rules

We used association rules mining in order to analyze the results obtained from the employed dataset that were used to develop and evaluate the product feature. The performance of this method was examined by measuring the effectiveness of the proposed rules to mine features and their corresponding opinions.

5.3.2 Sentiment Analysis using WordNet and SentiWordNet

In order to sentiment analysis we used WordNet and SentiWordNet. WordNet is a large lexical database of English created by Princeton University [2]. Nouns, verbs, adjectives, and adverbs are grouped into sets of conceptual groups. Adjectives are organized into synonym and antonym clusters with a given adjective. We can search the synonyms and antonyms of a word from the WordNet. SentiWordNet is a lexical resource for opinion mining. SentiWordNet assigns to each synset of WordNet three sentiment scores: positivity, negativity, objectivity.

5.3.3 Evaluation measure

As the baseline method mostly depends on manually extracted feature and opinion, the proposed method aims to automate the extraction process.We have performed experiments using reviews from different categories of amazon dataset. The dataset consisted of different categories like clothing, video games, baby products, and automotive.Each category consisted of positive, negative reviews. Positive and Negative Reviews were used to train the system and 25 known positive and Negative reviews were used for classification from which evaluation measures were calculated. For classification, True Positives (TP), True Negatives (TN), False Negatives (FN) and False Positives (FP) are used to compare the class labels (Positive and Negative) assigned to features by a classifier. True positive are terms truly classified as the positive. True Negative is the ones truly classified as Negative. Evaluation measures like precision, recall, F-measure, specificity and accuracy are easily calculated once we get the confusion matrix consisting of TP, TN, FP, and FN. Different evaluation measures we used for study are:

1. Confusion Matrix: Is the matrix which describes the performance of a classifier on test data for which the true values or actual values are known. Confusion matrix is helpful in interpreting the accuracy of the result for the given classification problem. Our resulted confusion Matrix shows in the Table 5.1.

2. Precision: It gives the fraction of retrieved instances that are relevant. Precision = Number of correct predictions/Number of predictions.

[2] https://wordnet.princeton.edu/

TABLE 5.2: Dataset statistics for a selection of categories on Amazon.

Category	Reviews	Users	Products
Clothing	19,16,306	10,60,278	2,306
Video Games	13,24,753	6,52,110	1,247
Automotive	13,73,768	7,52,110	1,047
Baby Product	9,15,446	4,52,110	567

TABLE 5.3: Evaluation of the Top 10 Features (Clothing) from 4875 Noun words using Association Rules

Noun	Frequency	Number of Reviews
costume	431	292
size	249	188
product	249	177
price	219	190
daughter	161	148
halloween	142	132
tutu	122	97
people	107	84
shirt	89	72
color	87	80

$$Precision = \frac{TP}{(TP + FP)}$$

3. Recall: Fraction of relevant instances retrieved. Recall=Number of correct predictions / Number of examples.

$$Recall = \frac{TP}{(TP + FN)}$$

4. F-Measure:Harmonic mean of precision and recall is calculated using F-Measure. The result is a score which is balanced between recall and precision. The formula used to calculate F-Measure is as :

$$F - Measure = \frac{2(Precision * Recall)}{(Precision + Recall)}$$

Table 5.7 shows an evaluation of the product features extraction, with the number of true extracted features compared to the number of manually extracted features from the baseline model. Also shows the performance of the proposed method via precision, recall and F-measure. It shows a significant improvement in precision in extracting relevant data, with an average precision of 76 percent in feature extraction and 56 percent in opinion extraction. On the other hand, there was an increase in recall, an average of 74 percent in features and a slight drop by 61 percent in opinion.

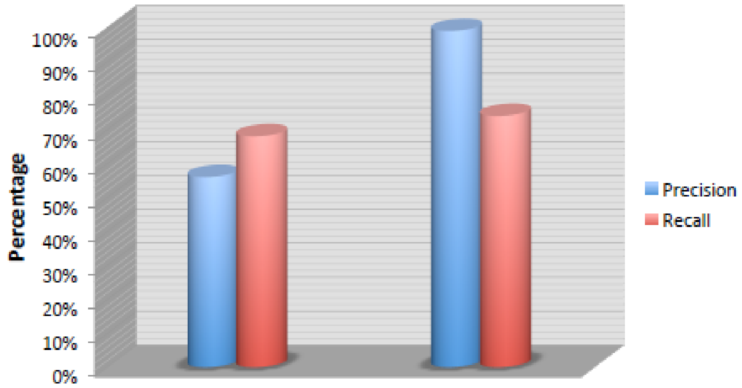

FIGURE 5.2: Manual and automated Feature extraction performance using Association Rules.

TABLE 5.4: Evaluation of the Top 10 Features (Video Games) from 12,259 Noun words using Association Rules.

Noun	Frequency	Number of Reviews
game	16370	2228
graphics	1990	698
character	1030	325
story	1028	346
controller	840	251
music	822	257
level	790	234
people	726	267
system	564	217
computer	464	167

5.3.4 Noun frequency and number of reviews

Extracted nouns which are more frequently talked about are usually genuine and important features or hot features. On the contrary, irrelevant contents in reviews are often diverse. Hence, those infrequent nouns are likely to be non-features or less important features. Table 5.3 and 5.4 shows evaluation of top 10 features for clothing and video games using association rules. Table 5.5 and 5.6 shows top 20 Manual features for clothing and video games.

Figure 5.2, shows manual and automated feature extraction performance using association rules, and the height of each bar is proportional to the recall and precision respective features. In Figure 5.3 as displayed by the graph above number of noun falling into different categories of number of reviews for clothing product, we placed x- axis number of nouns and y-axis number of reviews (e.g. 20 nouns appears from 10 reviews). In Figure 5.4 as displayed by the bar graphs above the most popular words, overall have to do with the clothing category, since this has the largest number of frequency in the reviews. As the same way, In Figure 5.5 as displayed by the graphs above the least popular words, overall have to do with the clothing category, since this has the lowest number of frequency in the reviews.

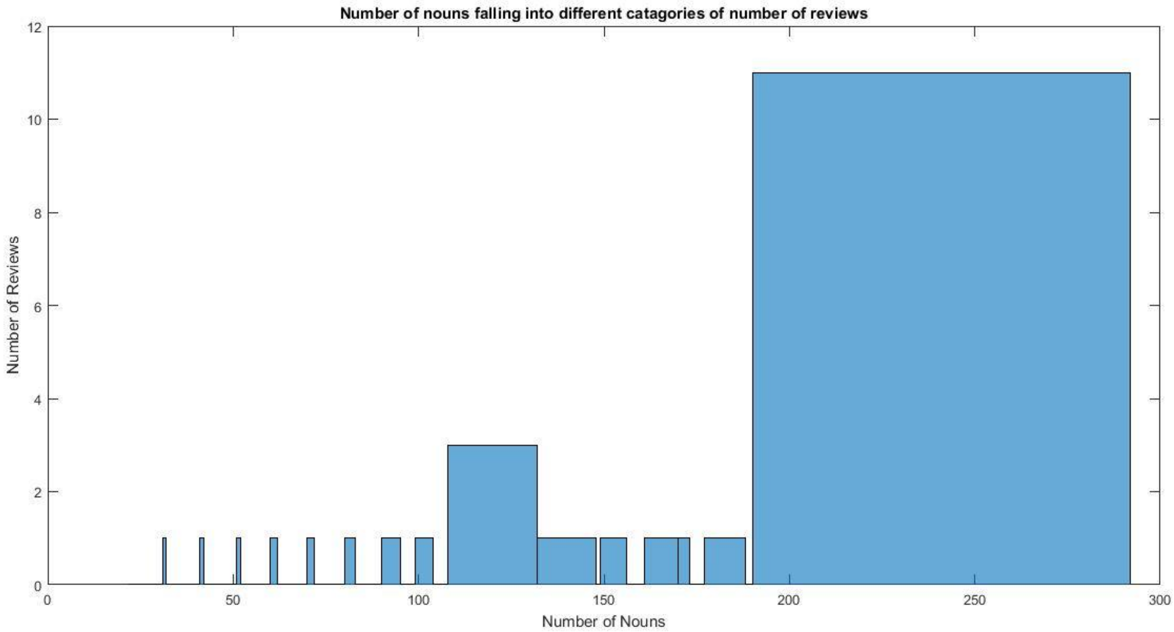

FIGURE 5.3: Number of Noun falling into different categories of number of reviews (clothing category).

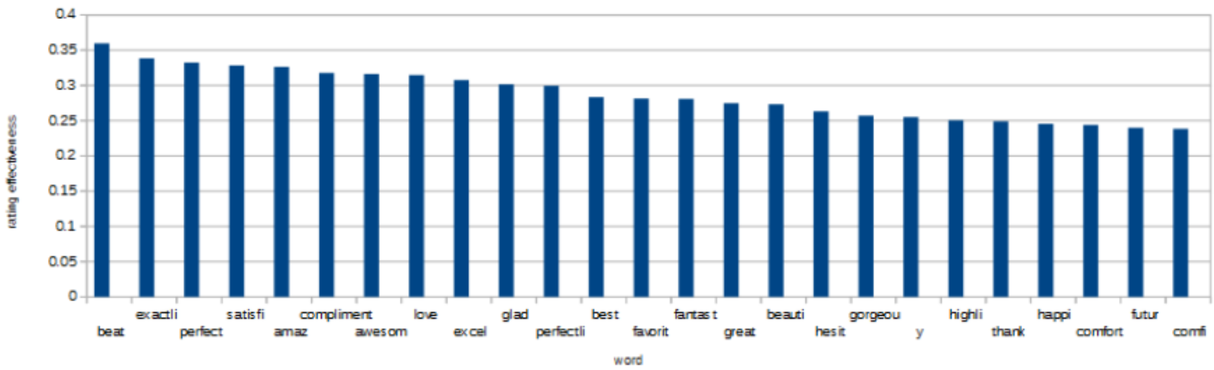

FIGURE 5.4: Shows the rating influence of the most popular features in the clothing category.

5.3.5 Positive and negative extracted features

In Figure 5.6 as displayed by the bar graphs above the most popular words, overall have to do with the baby-product category, since this has the largest number of frequency in the reviews from the rating. As the same way, In Figure 5.7 as displayed by the graphs above the least popular words, overall have to do with the baby-product category, since this has the lowest number of frequency in the reviews from the rating. In Figure 5.8 and 5.9 as displayed by the pie chart of top five hot features which influence in opinion (e.g. costume hold the greatest percentage rate and following size, product and quality features from clothing, on the other hand game hold greatest rate and following fun, graphics features from video games category).

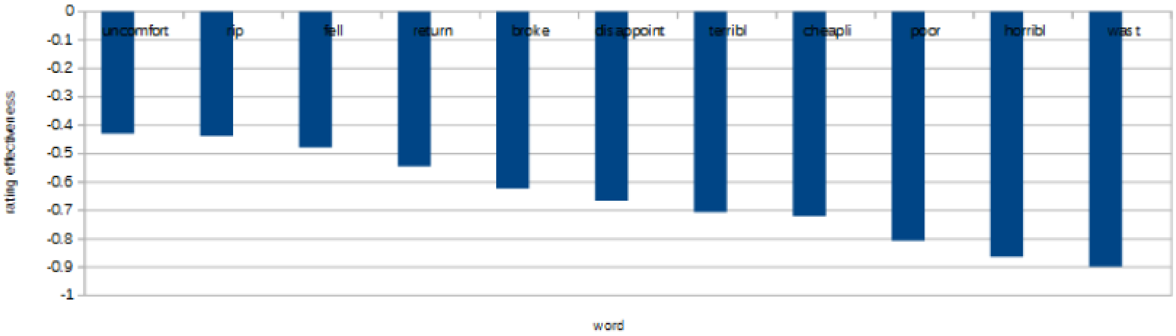

FIGURE 5.5: Shows the rating influence of the least popular words in the clothing category.

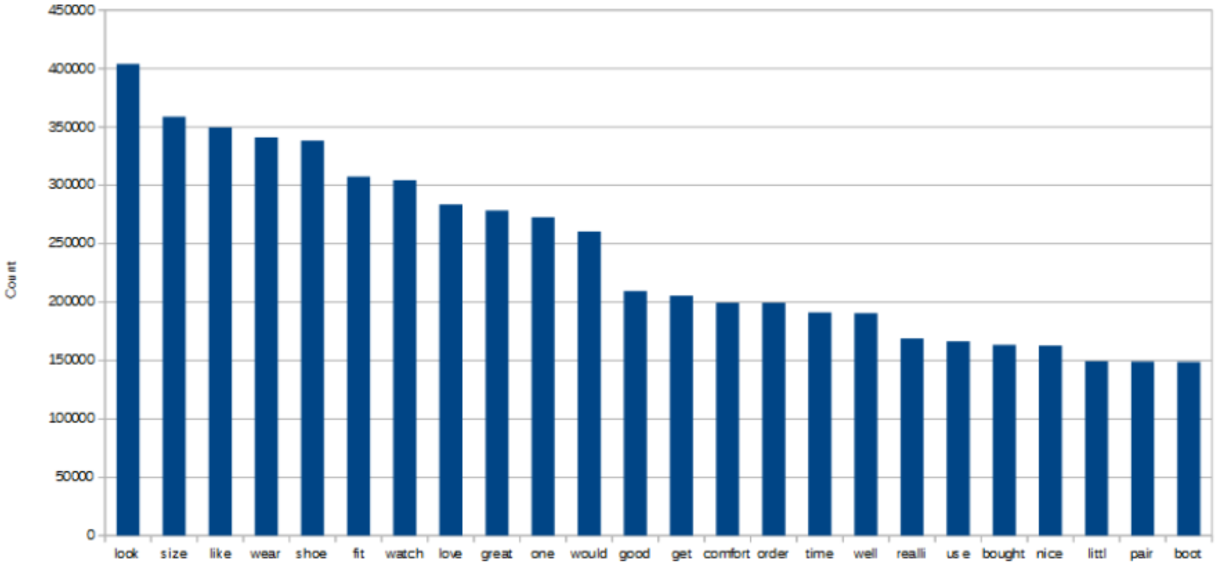

FIGURE 5.6: Shows the rating influence of the most popular words in the baby-products category.

5.4 Opinion Mining from reviews

Opinion Mining refers to the use of natural language processing, text analysis, computational linguistics, and biometrics to systematically identify, extract, quantify, and study affective states and subjective information. In table 5.8 and 5.10 as displayed as Positive and Negative

TABLE 5.5: Top 20 Manual Features for Clothing.

Features	Features	Features	Features	Features
costume	quality	tutu	color	party
price	daughter	box	child	purchase
size	halloween	gift	mask	dress
product	people	shirt	item	christmas

TABLE 5.6: Top 20 Manual Features for Video Games.

Features	Features	Features	Features	Features
game	controller	series	system	money
graphics	music	gameplay	computer	battle
character	level	version	mode	puzzle
story	people	video	adventure	enemies

TABLE 5.7: The Average Performance of Proposed Method using Association Rule Mining.

Average Precision		
	Feature extraction	Opinion extraction
Manuel	0.56	0.64
Proposed method	0.60	0.64
Average Recall		
	Feature extraction	Opinion extraction
Manuel	0.68	0.69
Proposed method	0.74	0.64
F-measure		
	Feature extraction	Opinion extraction
Manuel	0.60	0.64
Proposed method	0.74	0.66

TABLE 5.8: Positive and Negative sentiment score for Clothing Features.

Features	Positive Sentiment Score	Features	Negative Sentiment Score
music	0.21875	bomb	-0.0625
favorite	0.140625	battle	-0.125
player	0.01171875	fantasy	-0.0625
character	0.109130859375	action	-0.0013427734375
adventure	0.125	problem	-0.34375
agent	0.25	opinion	-0.4375
fan	0.03125	gold	-0.0625
sound	0.680908203125	brand	-0.046875
quality	0.40625	light	-0.162689395249
chance	0.0625	battery	-0.001953125

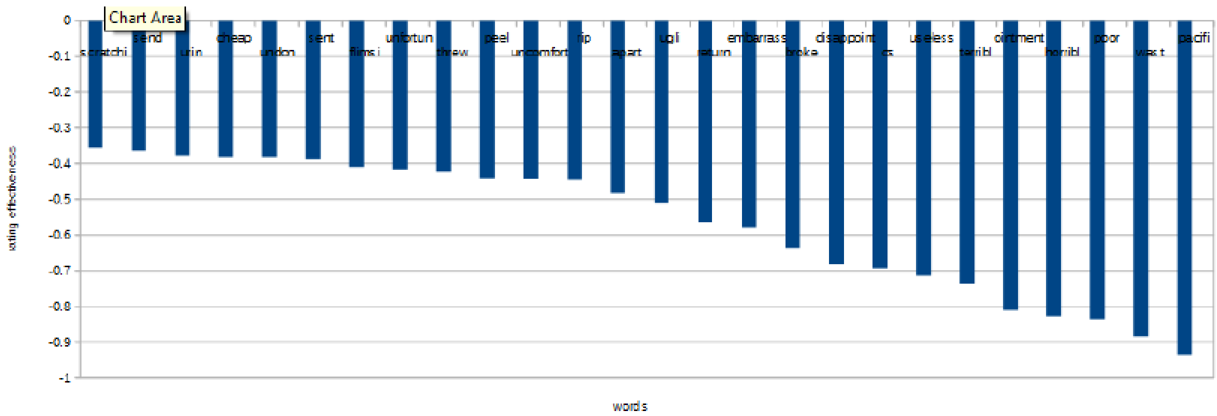

FIGURE 5.7: Shows the rating influence of the least popular words in the baby-products category.

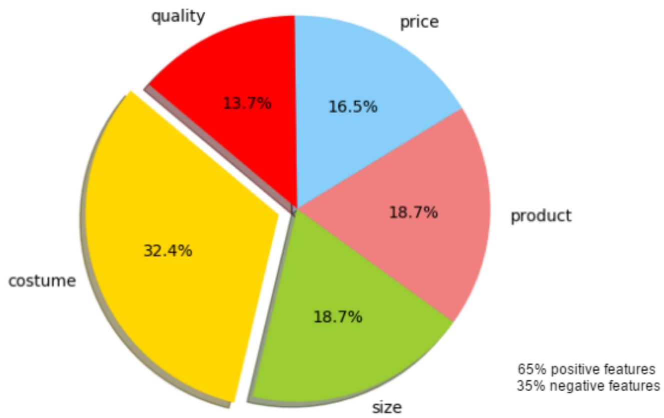

FIGURE 5.8: Shows top five features for clothing category in percentage.

sentiment score for Clothing and Video Games features. In table 5.9 as displayed, Positive and Negative sentiment score for Video Games opinionated features, e.g 'quality of tutu is great'. We get 'quality' from extracted noun feature and 'great' from opinion mining. From opinionated feature extraction, we consider noun features what we extracted from the review and associated opinionated phrases (adjective word). Every noun and adjective words of sentiment extracted above is then sent to polarizer that return (+ value) if the sentiment is positive else (- value) which means the sentiment is negative. We carefully chose affective words and general evaluative words for sentiment analysis. The sentiment analysis should not be feature-specific evaluative because they are assumed to be unknown which tends to extract subjective information required for source materials by applying natural concept of natural language processing.

TABLE 5.9: Positive and Negative sentiment score for Video Games opinionated features.

Features	Positive Sentiment Score	Features	Negative Sentiment Score
powerful	0.45175	dark	-0.0345
nice	0.7840625	old	-0.235
good	0.45171875	irritating	-0.435
great	0.7859375	normal	-0.006744375
excited	0.012785	disappointed	-0.124375
happy	0.00123	hidden	-0.006575
awesome	0.345316725	crazy	-0.03445
worth	0.00986803125	unhappy	-0.076875
massive	0.784086925	cynical	-0.0023395249
interested	0.00606725	complicated	-0.2351955

TABLE 5.10: Positive and Negative sentiment score for Video Game Features.

Features	Positive Sentiment Score	Features	Negative Sentiment Score
quality	0.40625	size	-0.0625
price	0.0390625	picture	-0.000732421875
color	0.3125	gift	-0.0625
fit	0.4375	problem	-0.34375
dress	0.125	order	-0.0001220703125
love	0.59375	costumes	-0.15625
band	0.00390625	brand	-0.046875
sound	0.680908203125	error	-0.46875
pattern	0.046875	copy	-0.0390625
usage	0.125	jacket	-0.03125

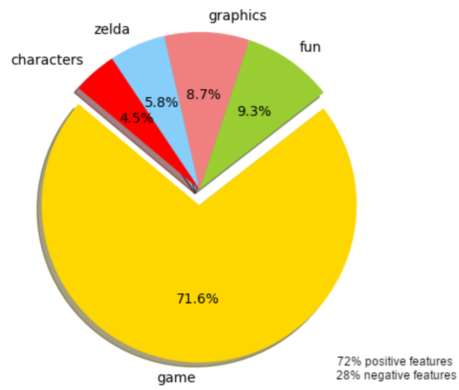

FIGURE 5.9: Shows top five features for video games category in percentage.

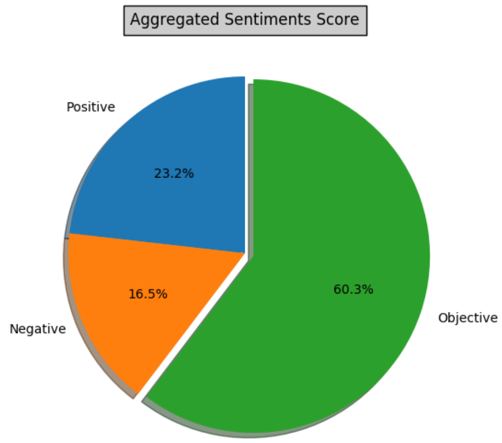

FIGURE 5.10: Aggregated Sentiments Score for Cloth category.

5.4.1 Extracting opinionated phrases

In Figure 5.10 as displayed by the pie chart aggregate sentiment score for clothing category, as we see objective score are greatest part from our study but objective score are negligible. In the following we can notice more positive score (23.2 percent) depicted in the pie chart and lower portion of negative score (16.5 percent) has been evaluated by using SentiWordNet. In Figure 5.11 as displayed by the pie chart as we can see positive sentiment score (23.9 percent) is greater portion in compare to lower portion of negative sentiment score (18.6 percent). In Figure 5.12 as displayed extracted opinion phrases by using Stanford CoreNLP parser. We have a set of product features from reviews and we need to identify the opinion words with respective feature that describe together. By using Stanford CoreNLP parser, we extract the adjectives that are within some fixed distance from each of the features words. Thus, we get a list of adjectives describing each of the features.

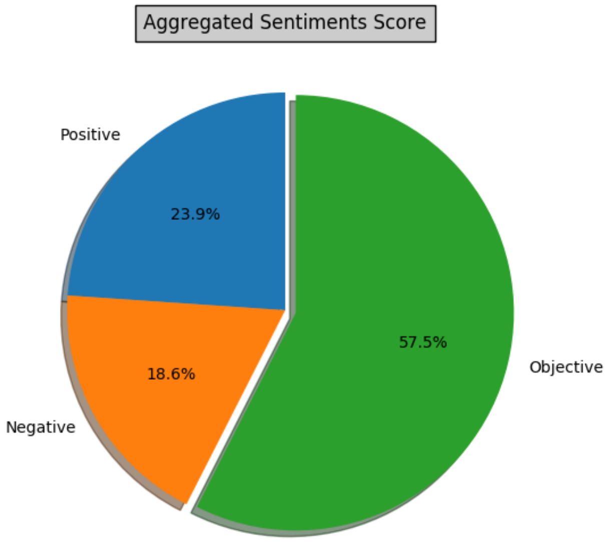

FIGURE 5.11: Aggregated Sentiments Score for Video Game category.

Review sentence	Opinion phrase
Thank you Halo Heaven amazing product for Little Girls. It is nice and full and the construction of the tutu is well done. This cute little tutu has held up through multiple wearings by a three-year old. Very good quality for a ballet style skirt. Unfortunately this style elastic is not stretchy enough to accommodate the 2-9 yr old range, this is CRAZY.	["product amazing", "tutu nice", "tutu cute" , " skirt good", "style crazy"]
This will be my second medal of honor I love how the incorporate real life military stories in the game great. I have played Zoombinis since I was a child and I still enjoy this game very much, I just wish it didn't glitch on newer software such as windows 7. Works great now me and my family cab have fun singing songs!	["game great", "game enjoy", "song great"]

FIGURE 5.12: Opinion phrases extraction using Stanford CoreNLP.

Chapter 6

Conclusions and Open issues

This chapter summarize the research presented in this thesis and discusses open issues. Mining opinionated product feature has become a fascinating research area due to the availability of a huge volume of user-generated content, e.g., reviewing websites, forums, and blogs. We exploited product features which were treated as features in the proposed feature spaces. The product reviews are about the products, so the product features should be good indicators in determining the sentiment types (positive or negative). The feature set was composed of nouns, on the other hand adjectives, which are generally considered to be related to opinion words. Our proposed method also finds the sentiment polarity of product features using Senti-WordNet and provides feature-based opinion mining from reviews. This thesis discussed the product feature extraction and mining opinions from Amazon reviews. The experiments were based on three different approaches: frequency based approaches where we performed experiment with association rule mining, relation-based approach where we extract features and identify sentiments of these features and opinions and finally we experimented with using Stanford CoreNLP parser in order to extract Opinion phrases.

6.1 Open issues

The factual research conducted throughout this thesis has laid the foundation for mining opinionated product feature from Amazon reviews using data mining and natural language processing techniques. These open issues can be the future work in the following areas:

Feature extraction using association rules, the aim is to extract all possible explicit features and identify implicit features in different word forms such as verbs, and then map the features to opinions. Nonetheless, more work needs to be done on implicit feature extraction, making it an interesting research direction in opinion mining.

More complex sentiments identification. Most sentiments are expressed through adjectives and adverbs. However, nouns (e.g., rubbish, junk, and crap) and verbs (e.g., hate and love) can also be used to express sentiments. Apart from individual words, there are also sentiment phrases and idioms, e.g., cost someone an arm and a leg. While identifying these types of sentiments are very difficult, the main challenge is predicting the polarity/rating of them.

Filtering comparative sentences, sometimes opinions are expressed in sentences comparing two items. Two main problems to be addressed are 1) identifying comparative sentences and 2) determining the preferred item. Although there have been some existing works, further research is still needed.

Evaluation of opinion phrases based on the likelihood of a held-out test set is applicable to data sets without such ground truth. However, this evaluation does not normally clarify the effectiveness of the opinion in terms of the accuracy of the extracted features and estimated ratings. Further research is needed in this area to find more application-oriented evaluation metrics.

Chapter 7

Implementation

This section describes the thesis implementation for mining opinionated product features from amazon reviews. The thesis implements Stanford Log-linear Part-Of-Speech Tagger, Stanford CoreNLP, Stanford Parser, JUnit, Java, Python, MySQL 4.1 and Mongo Java driver.

7.1 Pre-processing

POS Tagging. Part of speech tagging performed on each of the sentences, using the Stanford parser which is read from JSON file. Noun phrases also were identified and considered as a single term. We split text at periods and exclamation marks and removed some unimportant marks such as quotations and parenthesis. The way we include stanford NLP in our code: The library provided "tag" the words in string. That is, for each word, the "tagger" gets whether it's a noun, a verb etc. and then assigns the result to the word. To do this, we

```
try {

        JsonFactory jfactory = new JsonFactory();
        // Initialize the tagger
        MaxentTagger tagger = new MaxentTagger(
                "F:\\stanfordAnnotator\\models\\english-left3words-distsim.tagger");

        /*** read from file ***/
        JsonParser jParser = jfactory.createJsonParser(
                new File(fileName));

        // loop until token equal to "}"
            String asin = null; // asin
            String reviewId = null;
        while (jParser.nextToken() != null)
            while (jParser.nextToken() != JsonToken.END_OBJECT) {

                String fieldname = jParser.getCurrentName();
                }


    }
```

FIGURE 7.1: Code excerpt - Initialize tagger and perform Tokenization.

load tagger a "trained" file that contains the necessary information for the tagger to tag the string. This "trained" file is called a model and has the extension ".tagger". There are several trained models provided by Stanford NLP group for different languages. And, the we create a new Class and in its main method write.The MaxentTagger constructor takes the path to the model (trained file) as a parameter and we import the MaxentTagger in order to throws some exceptions.

```
/**
* takes noun phrases from review text and stop word list
*/
public static String [] partsSpeechTokens = {"NN", "NNS","NNP", "NNPS" };

//public static String [] asinList = {"B00LA89DW2","B00LBAM588" };//asin

public static String [] blackList ={"today", "january","sunday", "friday","day", "month","year","tomorrow",
        "afternoon","night", "monday", "tuesday", "wednesday", "thursday", "saturday","sunday", "february",
        "march", "april", "may", "june", "july", "august", "september", "october", "november", "december",
        "week", "year", "time", "weeks", "days", "years", "hours", "months", "hour","product" };

public static String fileName = "F:\\Thesis\\Amazon Dataset\\reviews_Video_Games.json\\reviews_Video_Games.json";
```

FIGURE 7.2: Code excerpt - Reading review from huge JSON file and stop words remove from sentences.

7.1.1 Data input and stop word removal

A subset of standard stop words (such as 'the' or 'this' or 'time' etc.) are also removed from the sentences.

7.1.2 Data cleaning

We performed stemming, punctuations removal, upper and lower cases adjustment, remove numbers, remove white space etc and finally write into csv file.

```
/**
* perform stemming, punctuations removal, upper and lower cases,
remove numbers, remove white space and finally write into csv file
*/
if(stringAndMarker!=null && stringAndMarker.length==2 &&  Arrays.asList(partsSpeechTokens).contains(stringAndMarker[1])){

        String rawText = stringAndMarker[0];
        rawText = rawText.replaceAll("\\p{Punct}|\\d",""); // removed all punctuation anywhere.
        rawText = rawText.toLowerCase(); // all are in lower case now
        rawText = rawText.replaceAll("\\d+",""); // removes any number anywhere.
        rawText = rawText.trim(); //white space removing
        if(rawText.length()>2 && !Arrays.asList(blackList).contains(rawText)){
            //writeToFile(fileName+"_out.csv",stringAndMarker[1]+","+rawText);
            if(uniqueKeySet.containsKey(reviewId+","+asin+","+stringAndMarker[1]+","+rawText)){
                uniqueKeySet.put(reviewId+","+asin+","+stringAndMarker[1]+","+rawText, uniqueKeySet.get(reviewId+
                        ","+asin+","+stringAndMarker[1]+","+rawText)+1);
            } else {
                uniqueKeySet.put(reviewId+","+asin+","+stringAndMarker[1]+","+rawText, 1);
            }
        }

    }
```

FIGURE 7.3: Code excerpt - cleaning data and write as output.

7.1.3 Schema of the database

After POS tagging and cleaned data we store noun words, adjective words into database table. We performed filtering in order to find out noun frequency and respective review number.

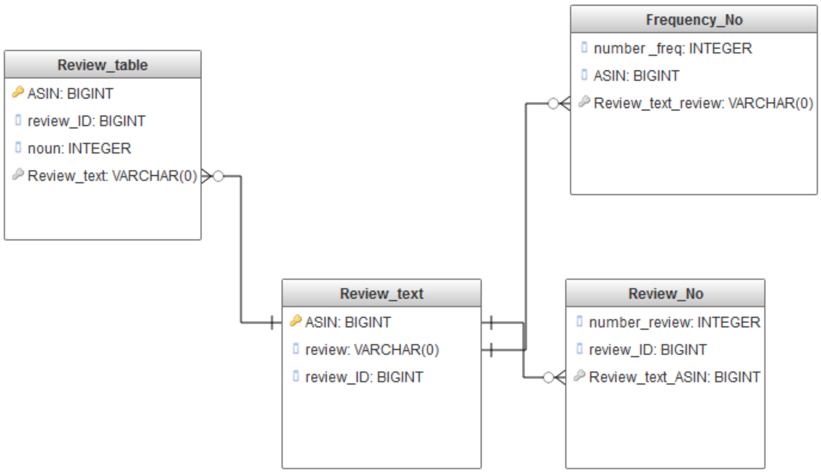

FIGURE 7.4: Code excerpt - Schema of the database.

7.1.4 Extracting product feature

In general, most product features indicating words are nouns or noun phrases. Therefore, after parsing the sentence, the next step is to identify a noun phrase as a product feature candidate. Algorithm 1 demonstrates the process to extract all the product feature candidates in reviews.

Algorithm for feature extraction and sentiment analysis.

1. Procedure to Review check()
2. ***begin***
3. ***for*** each reviews remove stopwords;
4. ***for*** each review r;
5. extract features f;
6. ***for*** each feature f value is (0,1);
7. value 0= Negative, Value 1= Positve;
8. vector generated for all f's against(0,1);
9. ***else if (c<0)*** check=negative;
10. ***if c>0,*** check=positive;
11. ***end for;***
12. ***end;***

7.2 Sentiment Analysis

For each feature we extract its sentiment from the review using POS tagging and ruled based extraction (using regular expressions). Each phrase of sentiment extracted above is then sent to polarizer that return (+ value) if the sentiment is positive else (- value) which means the sentiment is negative. We performed sentiment analysis with using Python libraries and SentiWordNet 3.0, which is a lexical resource for opinion mining. SentiWordNet assigns to each synset of WordNet three sentiment scores: positivity, negativity, and objectivity.

```python
"""
Class to score sentiment of word.
Use domain-independent method of dictionary lookup of sentiment words,
handling negations and multiword expressions. Based on SentiWordNet 3.0.
"""

import nltk
import re


class SentimentAnalysis(object):
    """Class to get sentiment score based on analyzer."""

    def __init__(self, filename='SentiWordNet.txt', weighting='geometric'):
        """Initialize with filename and choice of weighting."""
        if weighting not in ('geometric', 'harmonic', 'average'):
            raise ValueError(
                'Allowed weighting options are geometric, harmonic, average')
        # parse file and build sentiwordnet dicts
        self.swn_pos = {'a': {}, 'v': {}, 'r': {}, 'n': {}}
        self.swn_all = {}
        self.build_swn(filename, weighting)

    def average(self, score_list):
        """Get arithmetic average of scores."""
        if(score_list):
            return sum(score_list) / float(len(score_list))
        else:
            return 0
```

FIGURE 7.5: Code excerpt - Count sentiment score of word.

7.3 Extracting opinion phrases

In order to extract opinion phrase mining we need to Java, we also requires Stanford CoreNLP 3.4, Stanford Parser, JUnit and Mongo Java driver. First we have to put all dependencies into maven project then extract pattern from the sentences.

```java
public class Postprocess {

    public Postprocess() {

    }

    public List<Pattern> run(List<Pattern> patterns) {

        Properties props = new Properties();
        props.setProperty("annotators", "tokenize, ssplit, pos, lemma, parse, sentiment");
        StanfordCoreNLP pipeline = new StanfordCoreNLP(props);

        for (Pattern pattern : patterns) {
            Annotation annotation = pipeline.process(pattern.toSentences());
            for (CoreMap sentence : annotation.get(CoreAnnotations.SentencesAnnotation.class)) {
                    Tree tree = sentence.get(SentimentCoreAnnotations.AnnotatedTree.class);
                    int sentiment = RNNCoreAnnotations.getPredictedClass(tree);
                    for (CoreLabel token : sentence.get(CoreAnnotations.TokensAnnotation.class)) {
                        String lemma = token.get(CoreAnnotations.LemmaAnnotation.class);

                    }
            }
        }
        return null;
    }
}
```

FIGURE 7.6: Code excerpt - Extracting opinion phrases.

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Appendix A

List of manual features

costume quality tutu color party price daughter box child purchase size halloween gift mask dress product people shirt item game controller series system money graphics music gameplay computer battle character level version mode puzzle story people video adventure enemies picture price light pattern camera sweat cost color auto coat paint level weather mode quality material size jacket jumper tool plastic dishwasher color quality cloth memory food paper shop data height calendar baby sticker quality fabric street finger gift character costume language stone size product program way price software quality words daughter halloween son level tutu lot bag bit money people picture box something mask fun gift material shirt book lessons item color jewelry part computer pictures course school thing grammar word fit child times learning version everything head immersion languages anything piece vocabulary amazon work kids lesson purchase waist dress outfit party helmet anyone pants granddaughter room system husband phrases package love stars books idea color someone skirt laptop support method review voice headset recognition reviews speakers lots company fabric couple band wife baby boy mouse style mickey job shipping place point side microphone sock face children college plastic rules service kind person customer order example pieces minutes class seller niece stuff trip tutus speaker clothes programs buy look shirts store level hat issue broom alphabet back friend costumes reason pink everyone conversation audio star adult access experience type water space waste learner cost line tool pair eye process sentence help information approach products user size life hit half hole skill teeth phone pocket unit length shape bracelet music not leather jacket classes teaching play fan practice wish eyes home trial design while album option house user perfect shoes choice world teacher arm kid phrase photo hand adult amount complaint cd plenty waistband collection feature tshirt internet speech mac daughter dictionary value medium brand bottom section glue layer strap mine travel summer bottle gear purpose rosary parts date fine ear pockets guide need fun graphic zelda character story controller music levels lot level thing people world series gameplay version link video times things system player ocarina character computer everything weapons part control mode play something raider tomb playstation adventure price case money fan gaming battle puzzles enemies fantasy gamecube life sound crash kart action fighter fact storyline item card course mission quality window star race plot control movie street review reason kind legend memory screen super side controller item

Appendix B

Sentimental words

powerful dark nice old good irritating great normal excited disappointed happy hidden awesome crazy worth unhappy massive cynical interested complicated music bomb favorite battle player fantasy character action adventure problem agent opinion fan gold sound brand quality light chance battery moist synthetic good worth warmer comfortable positive nonstop special extra simple sharp fabulous bright nontoxic compact favorite disgusting handy significant decent outlander multiple difficult happy amazing smooth mediocre elastic disappointed adequate terrific efficient sharp helpful expensive fantastic heavy satisfactory great expensive outlander easy worth better near nice new decent multiple fewer despicable antitank difficult key happy easy reverse bright light incandescent pleased faster terrible outstanding blind little reverse reverse light good brighter much nice tinted great tinted cool tough good steep brighter correct pure incandescent original light white later new trim sweet sunbleached amazing good durable original great exact beautiful best great thin old great new nice top good satin black smooth awesome good interior several dark great lighter grey good usable many perceptible enough multiple essential other sure thin only durable clean bad solid many perfect same important interior normal first different personal long distant expensive much least worth smooth awesome retail mediocre best great many awesome heavy happy dry great lower only other different good better dry first large warm excellent less earlier ready dry right whole weird happy heavy impressed amazing small great happy elastic rainy next back snug tight great worth elastic lower crazy only expandable other north small ski main cold perfect comfortable elastic great high much dry big known other first open regular good same other left dry easier cool warm nice bthe smaller good inner dry durina waterproof useless same sure second dissapointed adequate overall nice several great handy wet second wet happy warm large kind recommend waterproof sick great great several happy first fine excellent durable dry good high yellow unusual tight nice sure first worth smallest bigger defective entire bright overall flexible better long adjustable superb wet lighter same general little good elastic comfortable huge tight zippered waterproof wider less second pant piece large fine good reasonable adequate green top onepiece corduroy great visible mild familiar full important other breathable highvisibility right acceptable snug only most inner reflective rear general local wet only several first clear proper big bulky nonsensical superb handy frustrating wrong bright yellow other several same local disapointed bright commercial several other same local slight original easy lighter great much happy hard long old easy great different good great durable heavy hard spiked good special unable weird larger real trim crappy right dull aware sticky good real bad little thin other sharp sure great black cant brown nice great happy happy meaner new key sure great natural enough awesome adhesive front slimmer great iffy larger regular hard slippery best good great several great other bad happy good slippery first spike great comfortable worth rough little long excellent much cheap cool hard great quick good easy tricky simple funeasy cool front handy great clear bright loose visible light regular sunny longer standard fine light old near good white bright dual rear dimmer regular big red easy fast super awesome bright standard new plastic bright few bigger sure reliable small nagging fine fitting enough old loose electrical left terrible bright standard current necessary good terrible horrendous brightest red bright normal much fine bright heavier subtle best overwhelming bigger perfect more nice good cute decent white free only bigger hard wrong noticable only unable due minor excellent thankful mixed bigger hesitant smaller other little big much larger second first small smaller good cute white durable bigger cute super tiny much small bright cute great easy larger little easy new more girly super fast fabulous pleased prompt perfect larger precious back sicker big correct unusual new cute smaller small awesome big each individual single little vibrant amazing accented smaller bright red great perfect extra bright high forgiving sticky less good nice easy better nice good blue white sexy happy white blue terrible nicer yellow much sharp easy bright satisfied blue free small hubby big perfect subtle big great overwhelming little smaller dark lasting great difficult sticky super fine good tough great boring decent right last great cheap nice good usual little good nice happy easy new used good different cheaper quicker blue lighter disappointed old beautiful much lame clean real nice heavy smooth vivid big worn additional free correct low great poor little gold blue small metalic other great sad white uneven dull more decal great lighter red little great patriotic american bigger sweet great actual good better hilarious high back sticky long great big conservative stiff easiest good tall awesome old top old perfect durable old great more same red terrible blue last correct orangish first better colorful other many happy yearsjust darker different good best same heavy sturdy better fine great few more proud vibrant good great good nicer poor last different better common sovereign great big thick darn awesome white great bland few top bright heavy much flimsy thin heavy satisfying new overall obnoxious good fine new great expensive only high nice good fast different general high good seprate pro more heavy terrific glad more accurate great new back great great bold high nice whole adhesive early thick intact more other great native fantastic unwanted beautiful fine such cool fantastic peaceful mandarin strong durable great great rear great heavy good red brown other several same free great good fading glad old clean crisp perfect real few more modern wellpriced accurate bold durable great proud long equivalent amateur single long great grand rear visual great awesome proud pleased great right nice bright other perfect other great military nominal good several great awesome great nice best strong proud wicked new good sharp high full happy full second heavy other much heavy original high great vigilant thick good great good such several short sweet satisfied available timely lousy unlimited next fine dangerous decal good durable bright good thick strong flybynight solid vivid good strong awesome clear positive easy political top great many numerous detailed stupid legit good yellow vast large bright local total thick bulletproof thin unscrupulous raw worthless low bright great thick good great good own hard few regular large bulky most fair slim cute much funny easier favorite smaller slowleaking handy several bright accurate first most dead builtin internal first terrible starter manual long last easy best sturdy great mopar first key amazing dirty small other noticeable front sharp aggressive easy great fit perfect new other reasonable high excellent real other regular similar ageold fascinating more pathetic overall brilliant flat best wrong good sticky recent young high first remarkable glad phenomenal same such huge great plastic steep little actual dead online worried glad fine dead lighter possible hokey most short finethe great much defective nice loud only own old standard excessivei available similar several convenient excellent few elastic short rectangular due other better wide secure front large entire easy small bad excellent top durable better less several back larger elastic empty easy wonderful similar liquid little only adjustable webbed easy dirty new drippy several easy super compact empty easy bottom little big empty mini easy small perfect same exact jealous noticeable worth good light okay black easy more easy durable elastic satisfied better empty appealing easy good compact new elastic great rolled valuable lame top easy cumbersome least old positive good few back regular expensive small worth small cute bigger long easy right personal elastic bigger sure top happy bigger easy top elastic bottom notorious empty best little great back top perfect great nice matching clean plastic fine other top removable best other easy bulky simple great small top slimline light best expandable gross sure easy great full back cluttered happy clear smaller better new more convenient bottom great convenient easy great grey satisfied black great adjustable huge small clean short long black easy tidy dirty great clean necessary convenient enough empty solid alternative elastic small great adjustable hard obtrusive only several larger large back workable considerable convenient small empty easy great unobtrusive easy other former big good enough top favorite long nice small easy empty hard convertible sticky easy useful good small empty wonderful interested skilled 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big certain further easy obtuse either skanky good technical nasty horrible usable only remote general excellent most average hard complex automotive starter additional busy great several soldering extensive able newer okay certain available cheesy electronic mixed silly

Appendix C

Example reviews

Under Armour makes great shirts. I usually order a size up so they fit loose.Great workout shirts (shirt//fit loose//great shirt). Size was a bit small but overall not too bad. Feels comfortable and is great for working out during the hot summer (size//small size//great). I wanted a tight fitting shirt and received a loose fitting shirt :(wish I would have received the right one because your stuff is too expensive to just sit in the drawer like this shirt does :(shirt//loose fitting// tight fitting// expensive shirt). These jack stands do what they are supposed to do. My Disco 2 is about 5,000 lbs and they hold it just fine. My only advice is that you make sure you know your vehicle height. These jack stands are tall. I use them on the lowest setting on my Disco and I still have to jack it up an inch or so to get it high enough to put these under. I will be lifting it soon though, so that will change, and hence the reason I got these (disco//vehicle hight//lowest setting). For a normal car though, these would probably not be my first choice. Also, if you are using them on asphalt, be aware that they might sink down into the ground a little. On concrete you wouldn't have this problem, but asphalt is soft enough that the edges of the stands might cut through. Finally, be safe and get a good pair of wheel chalks to use (only advice normal car). you can hardly find these in local auto stores and the ones the do sell cost just as much without the double locking ability and also are probably only 2 ton. I have a kid and I just don't think something holding so much weight should easily collapse with the flip of a lever (local auto// much weight//). These jack stands are awesome! I own a Chevrolet Avalanche Z71 and I can fit most standard jack stands underneath the frame without even jacking up the truck, so I needed jack stands that give me the high lift ability while still remaining stable. The lift range on these jack stands is great, and the build quality is very high(jack // great jack//standard great). I have complete confidence in these jack stands while working beneath the truck. Similar jack stands are well over 75 dollars. The additional safety lock is a great feature, especially if you have to work near the jack stand. It is a simple metal bar that slides in between the lift teeth, preventing the neck from lowering (awesome jack//most standard//additional safety). Built Well and A Great Price!Hard to mess up construction of a jack stand.These function as intended and have locks/blocks to keep the jacks from adjusting in the case you bump the drop lever(s).Enough Said (great price//intended function). Heavy duty, no flaws. Easy to use. Make sure you bend in the tabs to prevent the insert from falling out later. These are great(heavy duty//great use). After reading about a recent death by a car enthusiast working on his car using non-locking jack stands, I immediately decided to replace my non-locking jackstands with these locking jack stands. Non-locking jackstands can collapse if the adjustment arm is accidentally bumped and pose a hazard if you're under the vehicle.These jack stands are high quality and lock so they can't collapse accidentally when you're under the vehicle. If your jack stands don't lock you really should consider replacing them (car//non looking // jack stand// high quality). These are good jacks for a car or minivan with low ground clearance. Not the heaviest jack stand you'll find, but sturdy enough for cars or minivans and good value at the price (good jack//low ground//highest jack//good value). Rock solid - very secure holding the back axle of a 6,800 lb Chevy Tahoe.Easy operation.Good value for the low price (low price//good value). look very strong ,good construction i used it on my suv and works very good love the double safety lock(good construction//very strong). he jacks are clean looking and well made and my car was as solid as a rock when sitting on them. They lose one star because the locking key on one jack doesn't quite fit in the holes in the frame designed to receive it. I had to encourage it to work the first time with a few taps from a hammer(car//clean jack//solid car). I bought size 2 for my 8 year old daughter and she loves it! She wears it when she plays basketball and it gives her confidence (play//play basketball// confidence). My grandson wanted these hi-tops and we bought them online. They arrived right on time as expected and he loves them Now that he is a tween his look is very important as with most kids. We are a family of converse wearers as I am sure tradition will carry on (important tradition). These are great shoes! Not a lot of support and they run a half size large but they are classics (shoes// size large// great shoes). Sneakers from the past that have been reborn. Still stylish and comfortable. The best sneakers ever made. I wear them proud and loud (Sneaker// Still stylish//great shoes). Good, heavyweight denim, but the cut of the jeans is way too full, especially in the leg and even after washing. Was the design influenced by gang attire, like the super-full, deep crotch, short pants, teenagers waddle around in? If that's your style, then give the jeans a few more stars.But these pants are not for adult men, and I don't expect much use of them. Some warning as to the cut needs to be in the on-line pants descriptions (jean//heavyweight jean//good). The black and white socks were sized a bit too big (black and sock//white sock// too big).I purchased this gate and after a month the gate would not remain attached/connected. They told me to contact the manufacturer. VM Innovations sold me the product and collected my money so they should work with the manufacturer like most retailers do. Even Walmart returns defective products especially with safety concerns. I filed an A-to- Z claim with Amazon. I'm hoping Amazon steps up when VM Innovations has not. There is too many good companies that stand behind the products they sell and have good customer to buy from vendors like VM Innovations (CD//defective product//good companies).I began using this when my first daughter began to crawl. I liked that it was bigger than any playpen or playyard and could accommodate my growing daughter as well as her toys. It is easy to put together and I purchased an additional section to make it even larger. We have used it at home, at the beach, in the yard and as a barrier for both the Christmas tree and pellet (wood// christmas tree) stove to keep our little ones safe (toy //bigger toy// additional section). The Superyard gives our 9 month old plenty of space to play, compared to pack-n-plays. He is strong for his age, pushing and pulling at the sides, and can pull himself up holding onto the side, but it has remained stable. As to ease of use, it took me less than a minute to set up and start using - much easier to assemble and move around than traditional playards. I can move it from our living room to basement to back patio quickly. We also used it as a barrier around the TV when several toddlers were recently at our house. As long as you follow directions and use common sense, this is a great product (play//strong age//traditional playard). I bought this playard when my oldest daughter was born (8 years ago). She loved it!! I was able to get in the playard with her and play and she loved that. She never cried or felt closed in because the design is so open. I took it to the beach and put it right on the sand and she was just as happy as she could be. I've also taken it to the pool. There is nowhere this playard can't go! Now that I've had my second child (3 mos.) I've started putting him in it to keep the dog off him while he's laying on the floor playing with his activity gym. This playard in my opinion is priceless and there has never been a better baby product out there to keep your baby safe from household disasters and keep you sane from chasing them all over the house! Good luck with this product-I know you'll love it!!! (playard//baby product//better product).