

**MULTI CRITERIA DECISION MAKING APPROACH  
FOR PRODUCT ASPECT EXTRACTION AND  
RANKING IN ASPECT-BASED SENTIMENT  
ANALYSIS**

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**MULTI CRITERIA DECISION MAKING  
APPROACH FOR PRODUCT ASPECT  
EXTRACTION AND RANKING IN ASPECT-  
BASED SENTIMENT ANALYSIS**

by

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**PENDEKATAN PEMBUAT KEPUTUSAN PELBAGAI KRITERIA  
UNTUK PENGEKSTRAKAN DAN PEMERINGKATAN ASPEK PRODUK  
DALAM ANALISIS SENTIMENT BERUPA ASPEK**

**ABSTRAK**

Pengenalpastian aspek produk dalam ulasan pelanggan boleh mempunyai pengaruh yang besar terhadap kedua-dua strategi perniagaan serta keputusan pelanggan. Kini, kebanyakan penyelidikan memberi tumpuan kepada teknik pembelajaran mesin, statistik, dan Pemprosesan Bahasa Asli (NLP) untuk mengenal pasti aspek produk dalam ulasan pelanggan. Cabaran kajian ini adalah untuk merumuskan pengenalpastian aspek sebagai masalah membuat keputusan. Untuk tujuan ini, kami mencadangkan pendekatan pengenalpastian aspek produk dengan menggabungkan pembuat keputusan berbilang kriteria (MCDM) dengan analisis sentimen. Pendekatan yang dicadangkan terdiri daripada dua peringkat; iaitu; pengekstrakan aspek produk dan pemeringkatan aspek produk. Untuk peringkat pengekstrakan aspek produk, pendekatan tidak diselia dicadangkan untuk mengenalpasti aspek dan atribut yang berkaitan dengan produk domain tertentu secara matematik menggunakan fail perkamusan dalam WordNet. Penilaian empirikal terhadap pendekatan pengekstrakan aspek produk yang menggunakan dua set data ulasan dalam talian terkemuka iaitu untuk sistem yang diselia dan tidak diselia dari segi ukuran dapat-balik, ketepatan, dan langkah-F telah menunjukkan bahawa pendekatan kami mencapai keputusan yang kompetitif dalam pengekstrakan aspek dari ulasan produk, terutamanya untuk ukuran ketepatan. Pada peringkat pemeringkatan aspek produk, dua kaedah telah dicadangkan, disebabkan kaedah-kaedah tersebut berbeza dari segi kepentingan, untuk menyusun kedudukan aspek produk; iaitu, Subjektif TOPSIS dan IPSI-TOPSIS. Kedua-dua pendekatan ini menarafkan aspek-aspek berdasarkan tiga kriteria pengekstrakan secara bersama:

berdasarkan kekerapan, berasaskan pendapat, dan keberkaitan aspek. Pendekatan IPSI-TOPSIS dibezakan dengan teknik pemberat kriteria objektif dan bukannya pemberat subjektif yang digunakan dalam TOPSIS Subjektif. Untuk proses penilaian, kaedah pemeringkatan yang dicadangkan dibandingkan dengan pendekatan asas yang berbeza. Hasil keputusan perbandingan menggunakan kaedah penilaian NDCG menunjukkan bahawa dua kaedah penarafan yang dicadangkan mengatasi pendekatan asas dalam memberi keutamaan kepada aspek produk yang tulen dalam maklum balas pelanggan.

# MULTI CRITERIA DECISION MAKING APPROACH FOR PRODUCT ASPECT EXTRACTION AND RANKING IN ASPECT-BASED SENTIMENT ANALYSIS

## ABSTRACT

Identifying product aspects in customer reviews can have a great influence on both business strategies as well as on customers' decisions. Presently, most research focuses on machine learning, statistical, and Natural Language Processing (NLP) techniques to identify the product aspects in customer reviews. The challenge of this research is to formulate *aspect identification* as a decision-making problem. To this end, we propose a product aspect identification approach by combining multi-criteria decision-making (MCDM) with sentiment analysis. The suggested approach consists of two stages namely product aspect extraction and product aspect ranking. For product *aspect extraction* stage, an unsupervised approach is proposed for identifying explicit opinionated aspects and attributes that are strongly related to a specific domain product mathematically using lexicographer files in WordNet. The empirical evaluation of the product aspect extraction approach using online reviews of two popular datasets of supervised and unsupervised systems in terms of recall, precision, and F-measure, showed that our approach achieved competitive results for aspect extraction from product reviews, especially for precision measure. For product *aspect ranking* stage, two approaches have been proposed to rank the extracted aspects, as these aspects differ in their significances, namely Subjective TOPSIS and IPSI-TOPSIS. These two approaches ranked the aspects based on three extraction criteria jointly: frequency-based, opinion-based, and aspect relevancy. The IPSI-TOPSIS approach is distinguished by the objective criteria weighting technique instead of subjective weighting which is used in Subjective TOPSIS. For the

evaluation process, the proposed ranking methods are compared against different baseline approaches. The comparison results using the NDCG ranking measure revealed that the two proposed ranking methods outperform the baseline approaches in prioritising the genuine product aspects in customer feedback.

# CHAPTER 1

## INTRODUCTION

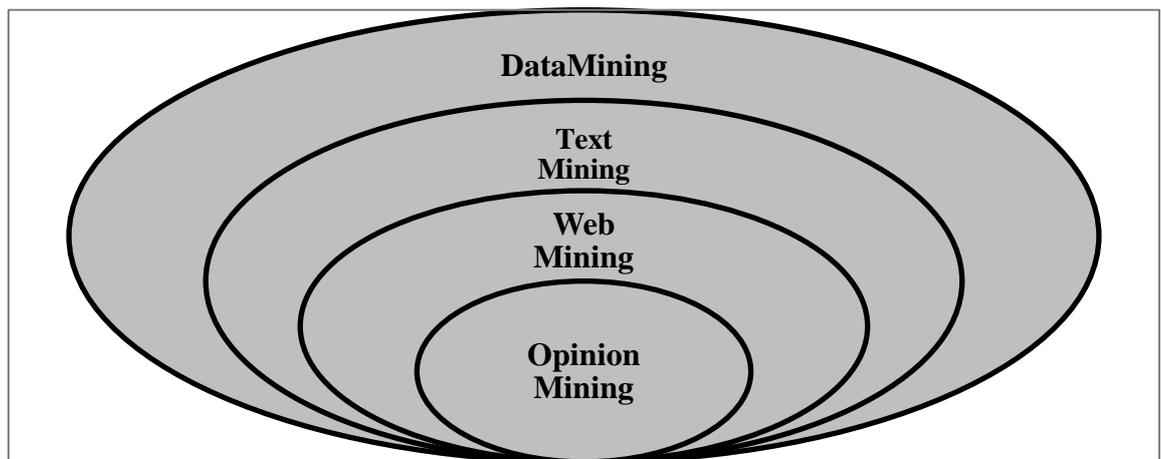
### 1.1 Overview

Social media such as Twitter, Facebook, forum discussions and blogs, have become a significant reference point for internet users. They have a profound influence on nearly all human behaviour, from customer comments regarding the best mobile phone to buy, to changes in the political situations of countries brought about by citizens, as in the case of some Middle Eastern countries (B. Liu, 2012). Customer reviews are considered a valuable source of information for businesses looking to produce products and services that meet customer needs. At the same time, these reviews assist probable customers in selecting the product or service that realises their expectations. For instance, travellers often rely on customer feedback from review sites such as TripAdvisor to select hotels.

Positive product reviews also play a powerful role in attracting new customers. According to independent market research company eMarketer ([www.eMarketer.com](http://www.eMarketer.com)), online users trust customer reviews 12 times more than the product details provided by businesses (Kavasoglu, 2013).

However, tracking and monitoring online opinions are difficult tasks because of the growing number of social websites and the huge amount of opinions published on each site. For instance, Twitter users publish more than 200 million tweets daily (Gao, Abel, Houben, & Yu, 2012), which is impossible to analyse manually. Thus, an automated treatment of opinionated information is necessary to help the average person identify relevant online reviews and extract opinions thereof.

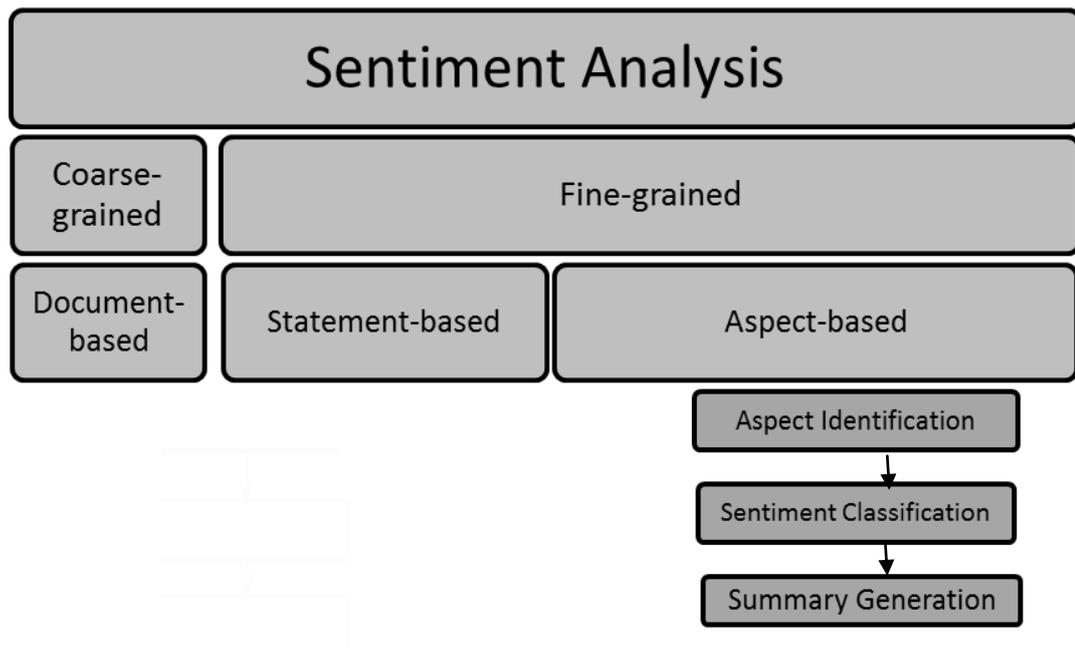
The computational treatment of opinions and subjective information on social networks involving entities such as people, events and products, is referred to as *sentiment analysis* (B. Liu, 2010a). Originally, the concept of sentiment analysis (or opinion mining (Hu & Liu, 2004a)) is related to natural language processing (NLP) and text mining. Also, it shares some characteristics of Web mining and information extraction, in addition to prediction analysis (Rashid, Anwer, Iqbal, & Sher, 2013; Raut & Londhe, 2014; Tang, Tan, & Cheng, 2009) (see Figure 1.1).



**Figure 1.1: Opinion Mining Hierarchy**

One year before the second millennium, the study of Wiebe, Bruce, & O'Hara, (1999) investigated the problem of subjectivity classification, in which they used statistical methods to classify subjective or objective sentences. For example, “*This camera is a Samsung product*” is an objective sentence, whereas “*I like this camera!*” contains an opinion and a personal belief such that it has been classified as a subjective sentence. As the years goes by, businesses and real life applications motivated the need for more research on opinion mining (B. Liu, 2012). Consequently, abundant research has been conducted to investigate the importance of sentiment analysis in almost every domain. To illustrate, (J. Liu, Cao, Lin, Huang, & Zhou, 2007) proposed a sentiment analysis approach to predict sales performance for a product. Also, (Tumasjan, Sprenger, Sandner, & Welpe, 2010) applied sentiment

analysis techniques on Twitter to predict election results. (Sadikov, Parameswaran, & Venetis, 2009) analysed movie reviews to predict movies ‘tickets sales. These studies and many others used the user generated contents on different social networks as a valuable source for business intelligence, mining views and attitudes (Tang et al., 2009).



**Figure 1.2: Sentiment Analysis Hierarchy**

Sentiment analysis (see Figure 1.2) has been investigated in previous studies using coarse-grained sentiment analysis and fine-grained sentiment analysis (Stoyanov, 2009). Coarse-grained sentiment analysis views the entire document as expressing a single opinion (or sentiment) about a single entity (Rashid et al., 2013). However, this type of analysis is inappropriate if the document contains multiple perspectives about manifold entities (Tang et al., 2009). By contrast, fine-grained sentiment analysis is focused on identifying the statements or aspects (features) of each entity mentioned in a document (B. Liu, 2012). This approach is more comprehensive than coarse-grained sentiment analysis because the extracted opinion

is not reflective of the entire document, but it could be for certain entities (e.g., a camera) and their aspects (e.g., battery life). To extract such details, a model of aspect-based sentiment analysis was introduced in (Hu & Liu, 2004a).

## 1.2 Aspect-based Sentiment Analysis

Aspect-based sentiment analysis aims to infer the aspects of target entities and the opinions expressed for each aspect in online reviews (Pontiki & Pavlopoulos, 2014). For instance, a review sentence like “*the iPhone’s call quality is good, but its battery life is too short*” contains two aspects (or sentiment targets) with different sentiments, namely “*call quality*” and “*battery life*”. This level of detail is required in various domains like restaurants, hotels, and customer electronics in addition to most industrial applications. Mainly, there are three essential tasks of aspect-based sentiment analysis as illustrated in Figure 1.3 (Ganeshbhai & Bhumika, 2015; Dingding Wang, Zhu, & Li, 2013).



**Figure 1.3: Aspect-based sentiment analysis tasks**

Briefly, aspect identification is an NLP task that computationally identifies the main aspects (or attributes) (like *camera zoom, battery life*) of an entity mentioned in Web reviews. The second task is sentiment classification which is the process of identifying the sentiment polarities (positive, negative, or neutral) toward each aspect of an entity. The last task is summary generation, where a comprehensive summary is produced from the extracted aspects and their sentiment polarities to identify the mood or orientation of reviewers regarding a specific entity.

In this thesis, we focus on the task of aspect identification which is considered the cornerstone of the aspect-based opinion mining problem (Ganeshbhai & Bhumika, 2015; Rana & Cheah, 2016). Specifically, this research targets online customer reviews which are considered a significant source of knowledge for potential customers and the business intelligence domain.

### **1.3 Motivation**

Customer reviews are necessary for e-commerce websites. Accordingly, most retail websites provide a platform for the customers to express their opinions or sentiments regarding various aspects of the presented products (Selvi & Chithra, 2015). Accordingly, it may no longer be needed for organisations to manage surveys to collect the customers' opinions about their products in order to measure the degree of customer satisfaction because such information is already available on the Web due to the explosive growth of social networks (B. Liu, 2012; Lu, 2011). Also, online user feedback comes with the advantages of real-time availability and no cost.

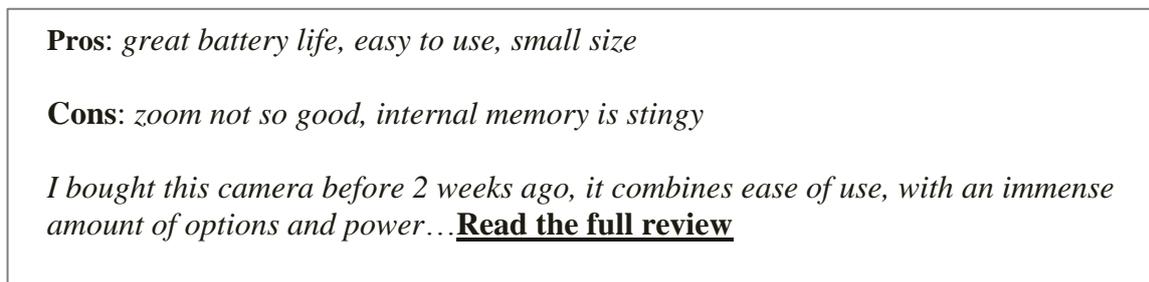
The massive growth of online opinions is overwhelming users and firms such that it has become a dreadful task to track the online reviews manually. To illustrate, CNet.com contains more than 7 million customer opinions regarding various products while Pricegrabber.com involves countless product reviews regarding 32 million products categorised into 20 categories (Zha, Yu, & Tang, 2014).

Generally, there are two formats of customer reviews on the Web (B. Liu, 2012):

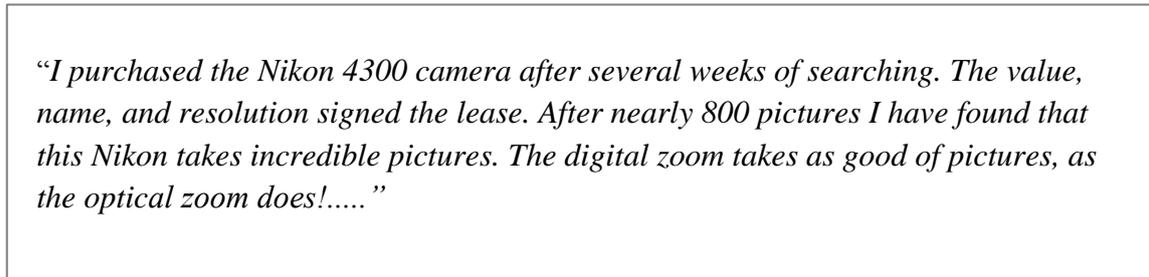
1. **Pros, Cons, with a detailed review:** In this format, the reviewer discusses the pros and cons of a product (or a service) followed by writing a detailed review. The reviewers should distinguish

between negative and positive feedback. This form of review is used in Epinions.com as shown in Figure 1.4

2. **Free format review:** The reviews are written in a free form with full sentences which may contain a combination of positive and negative comments. Amazon.com is a prominent example of this format as illustrated in Figure 1.5



**Figure 1.4: An example of pros and cons review format about a camera product**



**Figure 1.5: An example of free format review about a camera**

Extracting product aspects from pros and cons reviews is relatively easy because this format consists of short phrases. Whereas, the free format reviews consist of complete sentences, and the reviewers tend to use long sentences to describe their experience with the corresponding product. The product aspects extraction in the free format is more challenging because complete sentences in the customer review are more complicated and contain a lot of irrelevant information.

The valuable knowledge that could be extracted from such tremendous online reviews for both customers, as well as firms, has encouraged many researchers to design various approaches to process these reviews automatically. However, most such research focused on the techniques of identifying the product aspects and the users' sentiments regarding each aspect based on NLP and statistical techniques without any ranking and prioritising of critical aspects that have a great impact on the customers and firms decisions (Hu & Liu, 2004b; Popescu & Etzioni, 2007; Quan & Ren, 2014). Some of these studies consider the ranking process for the extracted aspects as a complementary task for the extraction process by ranking the candidate product aspects based on statistical information of their occurrences. The significance of these aspects differs in their influence on the customer satisfaction regarding a product. For instance, some aspects of *iPhone* like “*battery*” and “*usability*” are considered more important than “*usb*” and “*button*”. Furthermore, customers are looking for quality information in the Web reviews, and guiding them to pay more attention to the important product aspects will allow them to make a wise purchasing decision. Thus, it is necessary to consider both extraction and ranking tasks at the same level of importance because, among the numerous amounts of extracted product aspects from customer reviews, the most important aspects should be highlighted by the ranking process.

Motivated by these needs, this thesis investigates the task of aspect identification as a problem of two main correlative components, namely, product aspect extraction and product aspect ranking to maximise the value of the extracted information from online reviews for potential customers and firms.

## 1.4 Problem Statement

### 1.4.1 *Product aspect extraction*

In the field of sentiment analysis, it is assumed that opinions expressed in online reviews should have targets (Quan & Ren, 2014). These targets are called *aspects*. Aspect extraction is a complex task in sentiment analysis in which NLP methods should be applied to unstructured textual data to automatically identify product aspects (Siqueira & Barros, 2010).

Manually scanning customer reviews to extract relevant information is time-consuming and costly for both customers and firms. In (Hu & Liu, 2004b), the authors highlighted the importance of automatic aspect extraction from customer reviews, citing several reasons. First, we cannot rely on the names of aspects that have been provided by merchants because the customers may use different words for the same aspects in their comments. Second, customers may comment on some aspects that the merchant may disregard. Third, the merchant may intentionally hide weak aspects from customers. Furthermore, business managers view customer reviews as a valuable means of determining product aspects that are important to customers, allowing them to design efficient and focused marketing strategies (Vu, Li, & Beliakov, 2012).

Most sentiment analysis approaches are domain dependent (Khan, Baharudin, & Khan, 2014), and building an aspect extraction model for each domain is a complex and time-consuming process. Extending and fitting a domain dependent method to other domains is also extremely difficult (Quan & Ren, 2014). Thus, automatic extraction of product aspects is required to address the problem of specificity of domain dependent methods.

Moreover, in e-commerce websites, these product aspects have been associated with positive and negative opinions, indicating the customers' satisfaction with these aspects (Kavasoglu, 2013). These opinionated aspects are more likely to be the relevant aspects of a specific domain product (Eirinaki, Pisal, & Singh, 2012). In the literature, a few studies focused on extracting domain relevant product aspects from online reviews (Hai, Chang, Kim, & Yang, 2014; Quan & Ren, 2014). Most of these studies are based on comparative domain corpora to identify intrinsic product aspects according to their occurrences.

The success of such approaches is critical because they are based on two main factors; firstly, the accurate selection of the suitable domain-independent corpus which should be dissimilar to the domain-specific dataset in order to distinguish the domain relevant aspects, and the second factor is the sufficient size of this domain-independent dataset in order to compute the intrinsic and extrinsic domain relevancy of the extracted aspects (Hai et al., 2014). With these two factors, we argue that the identification of domain relevant aspects will be difficult especially in finding suitable dissimilar domain independent corpus, and this difficulty is more clear in the study of (Hai et al., 2014) which evaluated the proposed approach of IEDR in terms of F-measure against 10 domain-independent corpora to determine the most distinct corpus to the domain-specific dataset.

Thus, extracting opinionated aspects that are relevant to a specific domain product from online customer reviews without any use of comparative domain corpora becomes a necessity. Also, the extracted aspects should be relevant to the product which the customer is looking for. The majority of the product aspects are explicitly mentioned in online reviews (Khan et al., 2014), thus, our approach is used for explicitly extracting aspects.

### ***1.4.2 Product Aspect Ranking***

Generally, the main goal of aspect extraction task is to identify the opinion targets mentioned in online reviews, therefore, the extracted aspects may be in hundreds (Zha et al., 2014). Also, these aspects are not the same in their importance. Some of these aspects have a great influence on the potential customer's decision and the businesses' strategies for product enhancements (Martina, Famitha, & Anithalaskhmi, 2014). However, the manual selection of the most representative product aspects from the huge amounts of extracted product aspects in online reviews is a tedious and time-consuming task. Furthermore, it is difficult for the customer to make a comparison among the presented products without highlighting those critical aspects. Thus, prioritising the extracted product aspects mentioned in the customer reviews becomes a necessity.

The process of prioritising the most influential product aspects is called aspect ranking and is distinguished as a task of predicting ratings for the individual aspects that have already been extracted from the numerous online reviews to infer the most important aspects for customers and firms (Zha et al., 2014). Most of the studies investigated this task based on two main observations. Firstly, the essential product aspects are those that have frequently been discussed by customers in online reviews. Secondly, the product aspects that have been associated with opinions or sentiments in online reviews are considered important aspects. These two observations have been investigated to rank the extracted aspects based on probabilistic approaches (Zha et al., 2014). However, it has been acknowledged that identifying product aspects based solely on their occurrence is less suitable to highlight those truly

important and influential aspects. Similarly, opinion-based approaches may identify many domain irrelevant product aspects.

Even though these observations are essential in the aspect ranking process, neither of the previous observations have focused on prioritising the aspects (like battery life) that are relevant to a specific domain product (like camera) in which the identification process of product aspects could be seen as a domain dependent entity recognition (Quan & Ren, 2014). Therefore, there is a need for additional essential criteria to consider the aspect relevancy to the domain product. However, with these multiple observations that should be considered jointly as criteria for ranking the aspects a critical question that arises is:

***How is the product aspect ranking process accomplished by considering all these observations?***

Sentiment analysis alone is less suitable for this purpose because there are more than one criterion needs to be considered to identify the most important product aspects. Also, it is necessary to leverage the importance for each criterion. Furthermore, to consider all these criteria jointly, an aggregation method is crucial to optimise the role of the ranking criteria. Ranking the product aspects by considering all these extraction criteria simultaneously, therefore, calls for another methodology. The multi-criteria decision-making (MCDM) approach is relevant for addressing these points because its strength is in considering multiple criteria together.

## **1.5 Overview of MCDM**

MCDM is one of the most important branches of operation research that grew rapidly before the end of the 20<sup>th</sup> century (Dragisa, Bojan, & Mira, 2013; Nădăban, Dzitac, & Dzitac, 2016). It is concerned with providing computational

tools to support the subjective evaluation of a set of decision alternatives based on a set of performance criteria by a decision-making group of experts (Behzadian, Khanmohammadi Otaghsara, Yazdani, & Ignatius, 2012). Over the last few years, various MCDM methods have been developed with small variations in existing methods which created new branches of research (Velasquez & Hester, 2013). It is considered a highly reliable methodology for ranking multiple alternatives based on several criteria (Umm-E-habiba & Asghar, 2009). MCDM methods have been successfully applied in different areas of economics, energy management, transportation, human resources management, and other domains (Shih, Shyur, & Lee, 2007; Velasquez & Hester, 2013). Moreover, MCDM has outperforms other ranking approaches (like probabilistic approaches) by its ability to consider the importance of each criterion in evaluating the participated alternatives. Thus, this research regards the product aspect ranking process as a decision-making problem, in which several criteria participating in the ranking of the product aspects to prioritise the most critical aspects based on these criteria. To the best of our knowledge, no research has previously investigated the MCDM approach to address the problem of product aspect ranking as a decision-making problem. Motivated by these needs, the MCDM approach is explored as the cornerstone of our proposed approach to product aspect identification.

Among numerous MCDM techniques developed to address various problems of real world applications, this research examines the Technique for Order Performance by Similarity to Ideal Solution (TOPSIS). TOPSIS (Hwang & Yoon, 1981) is considered one of the most important MCDM methods used to solve multidimensional problems in the real world. It was originally proposed to

choose the best alternative based on a finite set of criteria. Recently, TOPSIS has been successfully applied to various domains of product design, manufacturing, quality control and others (Shih et al., 2007). We extended the application of TOPSIS to product aspect ranking to enhance the ranking process of the extracted product aspects from customer reviews by considering all the extraction criteria simultaneously.

## **1.6 Research Objectives**

The principal goal of this thesis is to address the problem of identifying the most important product aspects from online customer reviews by extracting and ranking the product aspects using sentiment analysis and MCDM. The new product aspect identification approach will enhance the usability of these aspects for both firms and customers. The following objectives can achieve this goal:

- To develop an unsupervised approach for extracting the opinionated product aspects automatically from customer reviews. This approach is capable of identifying the aspects that have been described positively or negatively in online reviews. Also, the extracted aspects should be more relevant to a specific domain product to be beneficial for customers and suit the customers' preferences.
- To develop a product aspect ranking approach distinguished by handling multiple extraction criteria jointly. The goal of the proposed approach is to consider the frequency-based, opinion-based, and the aspect relevancy criteria simultaneously in order to leverage the importance of each criterion in prioritizing the influential product aspects on the customers' decision of

choosing the best product to buy, as well as, in developing the businesses strategies to maintain the quality of the products .

- To develop a new MCDM method that aims to enhance the product aspect ranking process by addressing the problems of subjectivity in the criteria weighting process and the independence of these criteria which strongly affects the ranking of the alternatives. Thus, the goal of the proposed MCDM approach is to consider the interdependencies among the participating criteria in the decision-making problem to enhance the product aspect ranking process.

### **1.7 Research Contributions**

To the best of our knowledge, this thesis proposes a new approach for product aspect extraction and ranking using sentiment analysis and MCDM. For this, these two tasks are explored thoroughly.

Within the proposed approach, we have made the following contributions:

1. Unsupervised approach for automatically extracting the opinionated aspects of a product from customer reviews. Two major criteria have been proposed to extract the genuine product aspects. First, product aspects should be described positively or negatively by many customers to be considered genuine product aspects. Therefore, a weighting technique for each candidate aspect has been initiated to determine the extent to which a specific aspect has been opinionated in the reviews. Second, the extracted aspects should be strongly related to the product domain. To verify this, we extract mathematically the degree of correlation between each candidate aspect and the product name using the lexicographer files in WordNet.

2. A novel product aspect ranking approach has been introduced in this research that aims to support the customer with a ranked list of the most representative product aspects that have been identified in online reviews using sentiment analysis and MCDM. The proposed work has been decomposed into the aspect extraction stage and aspect ranking stage. The aspect extraction stage extracts three lists of the candidate product aspects based on three main extraction criteria: frequency-based, opinion-based, and aspect relevant based respectively. The second stage of this work is aspect ranking where the Technique for Order Performance by Similarity to Ideal Solution (TOPSIS) method has been investigated based on its popularity among other MCDM methods. TOPSIS has been exploited efficiently in this research by considering all the extraction criteria simultaneously to produce a ranked list of the most relevant aspects for a domain-specific product to be presented to the probable customers and the firms.
3. A new MCDM approach called IPSI-TOPSIS improves the process of traditional subjective TOPSIS method, where the criteria are weighted by human experts, by enhancing the weighting process of the participating extraction criteria in TOPSIS to make it a more objective and automatic weighting. The proposed objective weighting Interrelated Preference Selection Index (IPSI) is based on the degree of convergence in the performance ratings of the alternatives and their performances in the rest of criteria in order to consider the complementary relationship among the extraction criteria instead of considering the divergence among the criteria, which is the traditional assumption of most of MCDM approaches. The proposed approach enhances the product aspects ranking process and is

appropriate to support the customers and firms with a ranked list of the most representative product aspects in the customer reviews.

## **1.8 Thesis Outline**

This thesis consists of six chapters. **Chapter 1** introduces the background and motivation followed by the problem statement, research objectives and the contributions of this research. **Chapter 2** discusses the important concepts and terminologies of sentiment analysis and reviews the state-of-the-art product aspect extraction and product aspect ranking tasks which are the cornerstones of our proposed framework of product aspects identification. **Chapter 3** focuses on opinionated product aspect extraction of specific domains from customer reviews. In this chapter, aspect relevancy of a specific domain is computed mathematically using WordNet lexicographer files. **Chapter 4** addresses the problem of prioritising the most influential product aspects among the huge amounts of extracted aspects by a product aspect ranking approach using sentiment analysis and MCDM based on multiple extraction criteria. A new MCDM method is proposed in **Chapter 5** for ranking the extracted aspects by enhancing the weighting process of the extraction criteria. Finally, **Chapter 6** concludes this research and recommends possible directions for future work.

## CHAPTER 2

### LITERATURE REVIEW

#### 2.1 Introduction

People's opinions attracted researchers' attention only after the beginning of the second millennium. Bing Liu (B. Liu, 2012) explained that as being because of small amounts of opinionated data on the Web at that time. Ever since, this area grew rapidly to be one of the most important research areas because the significance of public opinions comes from its efficiency nearly on all human activities and almost all domains (like marketing, news, elections ...etc.), especially in the domain of customer reviews, where these reviews are important reference for both customers and businesses.

This thesis proposes a product aspect identification approach comprising the product aspect extraction and a product aspect ranking approach using sentiment analysis and MCDM. It focuses on addressing the key problems to build its approach ranging from extracting the opinionated product aspects that are relevant to a specific domain product using sentiment analysis to ranking the extracted aspects using MCDM to identify the most relevant product aspects in customer reviews. This chapter starts by canvassing the background of sentiment analysis and MCDM. Then, we move to aspect-based sentiment analysis to review a number of its applications and approaches. From there, we proceed to discuss the related works of the main components of our approach, whereby we focus on aspect extraction methods and aspect ranking approaches that have been designed in the literature.

## 2.2 Sentiment Analysis

Opinions are considered the main factor of controlling almost all of the human behaviours. Capturing the experiences and knowledge from others helps in making wise decisions. With the development of Web 2.0, people started sharing their opinions on the Web which creates the opportunity for exchanging experiences. The proliferation of people's opinions on various social networks in different domains has inspired many researchers to propose numerous approaches to mine the valuable knowledge from these opinions automatically to assist in the decision-making process, not only for probable customers but also for organisations.

The concept of sentiment analysis, which is originally presented in the study of Nasukawa (2003) has become one of the most important branches of NLP to analyse people's opinions, emotions, or beliefs to extract their sentiments regarding specific targets. "*Opinion mining*" refers to the same concept of sentiment analysis, and appeared in (Dave et al., 2003). Both concepts focus on analysing subjective information published on the Web, where this information is associated with positive or negative sentiments regarding different entities. However, the concept of sentiment analysis is commonly used in industry, whereas in academic research both terms are used interchangeably (B. Liu, 2012).

In the field of sentiment analysis, the concept of "*Opinion*" has been defined in (B. Liu, 2010b) as a model of five components  $(o_j, f_{jk}, oo_{ijkl}, h_i, t_l)$ , where  $o_j$  refers to the name of object or entity, which could be a product, service, organisation, or other objects.  $f_{jk}$  is a feature (or aspect) of the entity, such as "*zoom*", "*memory size*", "*battery life*" where these are considered aspects of "*camera*" entity.  $oo_{ijkl}$  is the opinion orientation of the feature  $f_{jk}$  which could be positive, negative, or neutral (no

opinion),  $h_i$  indicates the opinion holder, like person or firm, and  $t_i$  is the time of when the opinion is expressed by the opinion holder  $h_i$ . All components are vital in sentiment analysis, and identifying each component in this model represents a critical task.

The body of research has explored the problem of sentiment analysis at three levels of granularity, namely; document level, sentence level, and aspect-based level. Majority of studies focused on document-level sentiment analysis. This level considers a document as the basic unit of information, in which the task is to extract one sentiment (positive or negative) regarding the topic presented in the document. Most studies investigated document-level sentiment analysis as a process of classifying Web reviews into positive or negative opinions. For instance, (Pang, Lee, & Vaithyanathan, 2002) proposed a sentiment classification approach using machine learning methods of support vector machine (SVM) and Naive Bayes to classify movie reviews positive and negative sentiments. (X. Wang, Wei, Liu, Zhou, & Zhang, 2011) proposed a graph-based hashtag approach to classifying Twitter post sentiments, and (Kouloumpis, Wilson, & Moore, 2011) used linguistic features and features that capture information about the informal and creative language used in microblogs. (Becker, Aharonson, & Rd, 2010) showed that sentiment classification should focus on the final portion of the text based on their psycholinguistic and psychophysical experiments. (Tokuhsa, Inui, & Matsumoto, 2008) investigated emotion classification of dialogue utterances. They first performed sentiment classification of three classes (positive, negative and neutral) and then classified positive and negative utterances into ten emotion categories.

Additionally, many studies exploited advanced techniques to analyse sentiments at the sentence level. For instance, (Wilson, Wiebe, & Hwa, 2004) proposed a method for sentiment classification of nested clauses of reviews using a wide range of syntactic features to recognise the polarities of opinions. Also, (McDonald, Hannan, Neylon, Wells, & Reynar, 2007) proposed a model for jointly classifying sentiments in texts using standard sequence classification techniques that utilise a constrained Viterbi algorithm, which is a dynamic programming algorithm for finding the probable sequence of hidden states. Various levels of syntactic and lexical features were employed in (Jakob & Gurevych, 2010)) to propose a kernel-based machine learning approach to mine the opinions in the sentence level.

However, document level as well as sentence level opinion mining do not satisfactorily extract detailed information about what people like or dislike about each product aspect. Thus, more fine-grained analysis is needed, which is aspect-based sentiment analysis.

### **2.3 Aspect-based Sentiment Analysis**

As a result of insufficiency of both document and sentence levels to identify the opinion targets and assigning sentiments to these targets, aspect level sentiment analysis comes with three tasks to address these problems namely, aspect identification, sentiment classification, and summary generation (or Opinion summarisation) (Ganeshbhai & Bhumika, 2015).

Starting with the second task, sentiment classification has been investigated in the literature using supervised and unsupervised techniques. Supervised techniques are based on training data, and many approaches are based on parsing to discover the dependency in the process of classification. To illustrate, (Jiang, Yu, Zhou, Liu, & Zhao, 2011) developed a dependency parser to generate the dependency aspects used in sentiment classification. Other machine learning methods have also been employed in this task like Naive Bayes (Smeureanu & Bucur, 2012), support vector machine (SVM) (Valarmathi & Palanisamy, 2011), and neural networks (Socher, Huval, Manning, & Ng, 2012).

However, as earlier stated, supervised methods need to be trained by a data set which is a tedious and costly process. Unsupervised methods can be more efficient to be domain-independent (Anitha, 2013; B. Liu, 2012).

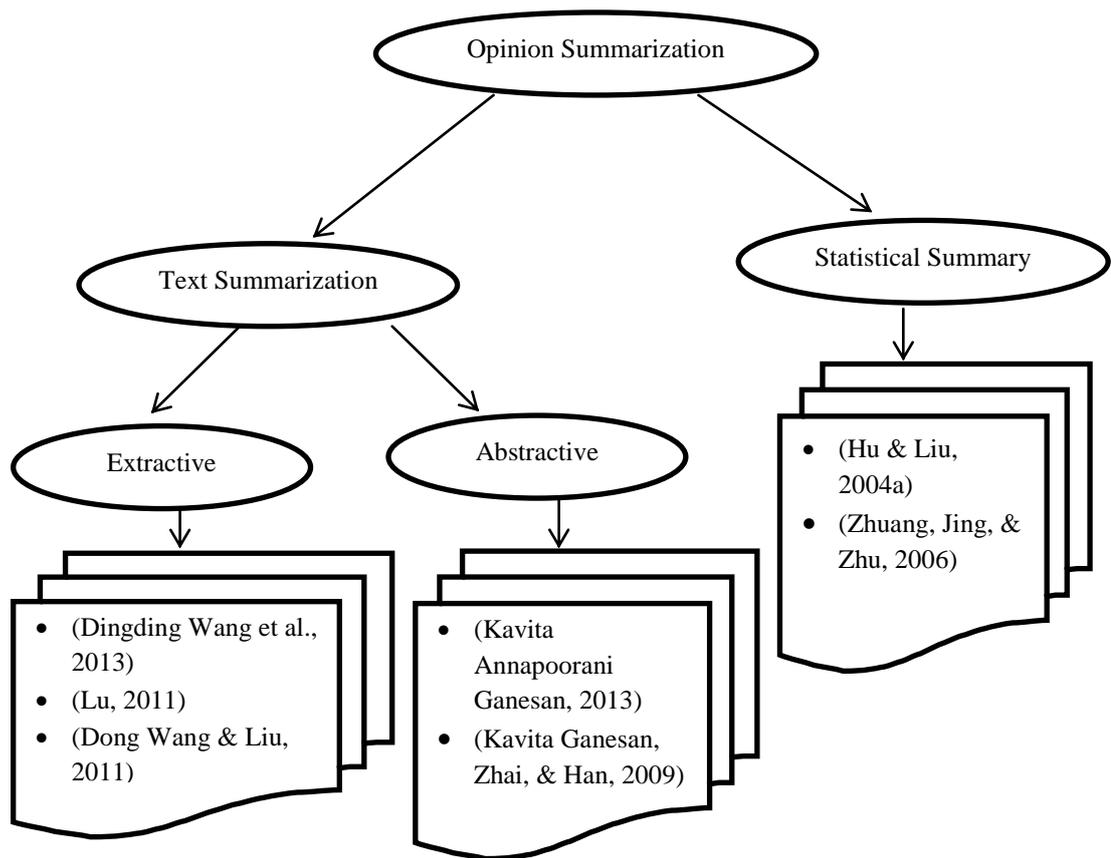
Unsupervised (lexicon-based) approaches are mainly based on sentiment lexicons, which contain sets of sentiments (mostly adjectives and adverbs). These sentiments are used to identify the orientation of each aspect in the customer reviews. In this type, there is no need for training the proposed techniques on a data set because the comprehensive lexicons which have been used (like WordNet) allow the unsupervised methods to perform well (B. Liu, 2012). For example, (Hu & Liu, 2004a) proposed a method for sentiment classification for the customer products using three steps. Firstly, all the adjective words that have been mentioned in the comments are extracted as these words represent the opinion words. Then, for each aspect in the sentence, the nearest adjective to this aspect is considered as its orientation. Finally, the semantic polarities for these adjectives are determined using WordNet by utilising the synonyms and antonyms of the adjectives.

Ding et al. (2008) improved the previous approach where the orientation of the opinion words are not only determined by one sentence, but also by exploring the orientation of these opinion words in other sentences and reviews by proposing a holistic lexicon-based technique. This work has been employed in many domains and performed very well (B. Liu, 2012).

Unsupervised approaches for sentiment classification are more efficient for different domains. Most of these approaches used lexicons of positive and negative words with a prior polarity without any requirement for semantic analysis. However, some of these lexicons have been built manually with a limited inclusion of opinion words (Gatti & Guerini, 2012). To tackle this problem, many approaches used a lexicon with a broad coverage of opinion words, which contains almost every emotional word in the English language such as SentiWordNet (Esuli & Sebastiani, 2006).

SentiWordNet has been built semi-automatically from a WordNet lexicon using a combination of linguistics and quantitative analysis, in which each word in a WordNet lexicon has multiple senses. SentiWordNet assigned numerical values (between -1 and 1) indicating the polarities of these senses (Gatti & Guerini, 2012).

The third task of the aspect-based model is a summary generation (or opinion summarisation) which has been defined as an aggregation of the online opinions and generating a summary to describe the representation of these opinions (Stoyanov, 2009). Most of the state-of-the-art of opinion summarisation used either traditional text summarisation or statistical models to generate a summary (see Figure 2.1).



**Figure 2.1: Opinion Summarization Models**

In brief, text summarization presents excerpts of opinions related to an aspect whereas statistical summarization presents quantified information regarding an aspect to the customer. For the latter, by quantifying the customer opinions, the customer can easily make a decision regarding a product. Hu and Liu (Hu & Liu, 2004a, 2004b) are considered pioneers in generating quantitative summaries for customer reviews by identifying the number of positive and negative customer reviews for each feature of a product separately, as illustrated in Figure 2.2.

<i>Digital_camera_1:</i>		
picture quality:		
Positive:	253	<individual reviews>
Negative:	6	<individual reviews>
size:		
Positive:	134	<individual reviews>
Negative:	10	<individual reviews>
...		

**Figure 2.2: Quantitative Summary by Hu & Liu**

The last task of aspect-based sentiment analysis and a key problem investigated in this thesis is aspect identification. The task of identifying the aspects from online reviews is a fundamental problem in aspect-based sentiment analysis (Quan & Ren, 2014). It is the most challenging problem among all other aspect-based sentiment analysis tasks (Rana & Cheah, 2016) because identifying opinions whose targets are not defined are restricted to use by customers and businesses. Moreover, opinion targets are represented as a set of aspects or entities in many applications (Ganeshbhai & Bhumika, 2015), specifically e-commerce applications. Many researchers have explored the problem of aspect identification with limited success of identifying the relevant aspects mainly in the domain of product reviews (Quan & Ren, 2014). Thus, we consider this problem important. In this research, the problem of aspect identification has been decomposed into aspect extraction and aspect ranking.

## **2.4 Aspect Extraction**

Aspect extraction is one of the most complex tasks in sentiment analysis, in which NLP methods are applied to unstructured textual data to automatically extract representative aspects (Siqueira & Barros, 2010).