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A Study on User Requirements Extraction and Cultural Attributes for Product Design

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Doctoral Dissertation

A Study on User Requirements Extraction and Cultural Attributes for Product Design

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Knowledge Science
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To My Family

Abstract

User requirements play an important role in Product design as which often to be used for supporting designers in terms of determining appropriate product's features for the design process. Furthermore, it can be considered as the goal for designers in designing products. Current approaches to obtaining user requirements typically use some traditional methods such as surveys, questionnaires, and interviews. These methods can gain some important information about products by interacting with customers directly or indirectly. However, the methods have some drawbacks as described as follows: First, it is clearly that obtaining the user's information in such a way is expensive.

In addition, it is difficult to obtain a large number of users' information by using traditional methods because we can only access a limited number of users due to time consuming and geographical distance. Furthermore, sometimes we cannot get the user's real emotions. Therefore, the obtained information could not reflect all aspects of what users need. Meanwhile, the information about products on the web is available and growing rapidly. The information comes from a very large number of users in different cultures and environments. This information is an essential knowledge for the new users when they would like to purchase the product. Thus, it is important information for designers in designing attractive products for users.

This thesis presents a method for bridging user requirements to designers in Product Design. The motivation behind this method is that user requirements are automatically collected by performing an opinion mining method on a set of online product reviews, which is available on the web. The user requirements are then provided to integrate with designers. In the thesis, we investigate various ways to extract user opinions from customer's opinions for designers in terms of designing products. The first work is to investigate in the review comments about whether or not helpful reviews can contribute to the early process of designers. We also consider the method to extract keywords automatically and investigate whether or not their extracted keywords can contribute to the early phase of product design. The proposed model has the following major steps: The first one is classifying irrelevant product reviews. We applied machine learning and deep learning methods for classifying irrelevant product reviews. The second one is to identify whether or not a review is helpful using deep learning techniques. The third one is a model of opinion extraction that extracts user requirements about the product.

We propose a novel method using opinion summarization methods, along with the use of keyword extraction to obtain user requirements. We propose helpful review detection and framework for utilizing keyword extraction in product design. In addition to that, we propose a deep learning model for sentiment classification and aspect sentiment classification and considering them as reference information The last contribution to study other contributions which aim at considering the cultural attributes and its impact on product design in the early process. We investigate how cultural attributes can be able to change and effect on selecting design concepts. A case study with designers showed the contribution of cultural attributes and user requirements in culture-oriented product

design.

Keywords: Product Design, User requirements extraction, Cultural Attributes, Opinion Mining

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Chapter 1

Introduction

Product design plays an important role in product development. The definition of product design can be expressed as follows "Product design is conceiving and giving form to goods and services that address needs.". Product design process is the set of strategic and tactical activities, from idea generation to commercialization, used to create a product design. In a systematic approach, product designers conceptualize and evaluate ideas, turning them into tangible inventions and products. Understanding user requirements (or User needs) are key component in Product Design process.

The user requirements can be used to help designers to determine the product's features for the design process. Besides, it can be considered as the goal for designers in designing products. Current approaches to obtaining user requirements usually use some traditional methods such as surveys, questionnaires, and interviews. These methods can gain some important information about products by interacting with customers. However, the methods have some drawbacks as described as follows: First, it is clear that obtaining the user's information in such a way is expensive and takes time. Also, it is difficult to get a large number of users' data by using traditional methods because we can only access a limited number of users. Furthermore, sometimes we cannot get real emotions of users. Therefore, the obtained information could not reflect all aspects of what users need.

On the other hand, the information about products on the web is available and growing rapidly which is updating and accessing by many users. The user's information about the product comes from a very large number of users who might be in different cultures. This information from the product's review is an essential knowledge for the new users when they would like to purchase the product. Thus, it is important information for designers in designing attractive products for users.

1.1 User Requirements and Product Design

Product design is the process by which it can be included in the product various forms, such as new features / functions, new look / feel or new technology. New features are the key source for product development in maintaining or increasing market share [43].

IDEO[1] is one of a great illustration for applying design in product innovation.

User requirements can be understood as the important information in user experience which plays an important role for product design [18][77][73][8]. Another illustration is the success of considering user experience in designing the iPhone as mentioned by (Donald A. Norman, 2005) *"One of the interesting things about the iPod, one of the things that people love most about it is not the technology; it's the box it comes in. That's because Apple understood that the iPod was not about the iPod; it was about the entire range of experience: the way they design their stores, the box it comes in, the iTunes website, the ease of getting the user back and forth." (Donald A. Norman, in Zachry, 2005).*

The challenge is how can we capture useful information within the user experience, for adding new features/functions, new look/ feel or new technologies for existing products. Fortunately, with the development of web services such as Amazon[1] and eBay[2], we can easily access a vast user's opinion of users' information for a product. Obtaining useful information for the design process is, therefore, a challenging task for design innovation[43]. However, there is a lot of redundant information relating to products by users. This motivates us to develop a method for obtaining useful opinion information for a given product. Our goal is to analyze users' aspect for designing product innovation and focus on how useful information relating to users and products can be obtained.

1.2 The Needs of Processing Product's Review

With the advantages of the development of computer science and technology, we could easily collect customer information on a large scale for providing to the process of product development. The customer relationship management technique (CRM) [7][44] is one of the method for collecting customer information. Besides, the statistical survey can be considered as a suitable method for widely applying to gather customer information and study behaviors of the customer. [2].

There are some previous studies attempt to utilize customer information by considering numerical and categorical data, but it is just used for a product recommendation, personalization, as well as analyzing factors for enhancing customer loyalty[53][50].

On the other hand, we are living on the age of "big data" in which textual data plays a significant part in customer information. The researchers start to use natural language processing techniques to extract information from text and got promising results [53][55][89][34]. The difficulty of dealing with textual data is that it is usually stored as unstructured free texts or semi-structured data. The handling of textual data is challenging and difficult tasks [29].

With the growing rapidly of e-Commerce and e-Business, it is common that customer often use online shopping sites such as Amazon.com and Walmart.com to find and buy products.

[1] http://www.ideo.com/contact/IDEO-FactSheet.pdf

[1] http://www.amazon.com/

[2] http://www.ebay.com/

Customers are invited or spontaneously participated in writing reviews to share their experiences, opinions, and suggestions for various products. Some consumers even act professionally to compare various similar products from different brands and comment on their pros and cons.

Customers often received the vote from other customers for helpful sharing, and they can become top customers of Amazon, which means that their opinion is influenced, other peoples.

These product reviews are invaluable to designers and manufacturers to better understand their customers' concerns and make improvements accordingly. However, analyzing and processing such valuable information is a challenging task. Because the number of customer reviews can increase rapidly, reading through them all manually is quite time-consuming. How to deal with large numbers of customer reviews and extract useful information from them has become an important but challenging task.

Many previous works have been reported dealing with online customer reviews. Most of them focused on opinion mining [34][5][16][61][45] including classifying reviews into positive and negative comments. More recently, the researchers in the AI community start to extract the salient topics and concerns across different review articles. The heart of technology is applied text summarization techniques performing on customer reviews [35][83][76][89].

However, the connection between the summarization results and designers is lack, and there is no special treatment for mining opinion reviews from "lead users".

Besides that, with the development of artificial intelligence (AI) (deep learning) and big data, the accuracy of opinion mining is improved, so we are able to exploit these tools for extracting user requirements to support designers. However, adapting these methods to extract useful customer information to support designers is still a challenging problem. In this study, we aim at developing a method for gathering customer requirements from multiple online customer reviews using appropriate automatic text summarizing.

1.3 The Important of Cultural Aspects for Product Design

The user requirements can be different from country to country due to the difference in culture. Design studies have shown that cultural aspects can be seen as important factors for developing products from country to country. Culture, design, and interaction make for an exciting research topic in this globalized world. Users are increasingly looking for differentiation in the products they own, as shown by Delaney et al. (2002)[17] and [62] Aula et al. (2003).

1.4 Aim of this Research

Creativity is a core of design process and is an essential part of innovation; it is the point of departure and often plays the key role in the innovation process. One of the big concerns for many companies is therefore how to generate more creativity. According to [3][77], the development of a product requires identifying customer needs, establishing target specification, generating and selecting product concepts, and testing product concepts. Based on this analysis, a study on identifying customer needs, to establish target specifications, and generate and select product concepts should be conducted. Therefore, analyzing user's opinion for current products is very essential to enrich creativity space for designing new products. Opinion extraction techniques [34] serve as a key to solve this problem.

We can obtain user's opinions about products through the feedback. It is essential to improve the quality of products by considering the advantages and disadvantages features of products. For example, designer groups of a company may take into account the user's opinions to extract useful information to improve the products.

In addition, the opinions regarding products are very useful for those who are potential users, so they can easily read the opinions to decide which products they would like to purchase. In addition, the products with high quality will be attracted a lot of buyers.

Therefore, obtaining user's opinions about products is very necessary for enriching creativity space in designing a new product. And it thus leads to the contributions in product development.

However, since for each products there are a lot of opinion documents, it is difficult to know whether or not a review document is useful for users, as well as for the purpose of design. In addition, it is very time consuming for designers to read all the opinion documents.

The motivation of this work is to focus on how useful user opinions are gained in order to support designers for designing product. With this in mind, I focus on a method that automatically obtains user requirements by extracting online product reviews. The proposed model has three major steps: The first one is classifying irrelevant product's reviews. We applied machine learning methods for classifying irrelevant product's reviews. The second one is that there are some reviews are not helpful for other customers, so we would like to recognize helpful reviews for being used with designers. The third one is a model of opinion extraction that extracts user requirements about the product. We propose a novel method using natural language processing method along with the use of topic identification to obtain user requirements. In addition, we also use the advance technique in computing text similarity between two sentences,in order to enrich linguistic information for the process of opinion extraction. The last model is to extract expert's reviews among set of review documents. In addition, we also aim at extracting positive and negative reviews and let designers know these information because sometime, negative comments would help to improve products. Last but not least, unlike previous work, we also think that obtaining the information from "lead users" are very important. Then, we develop a simple techniques collecting all reviews of the lead users in amazon website. We extract the user requirements from lead users and bring it to designers.

Furthermore, we would like to study the contribution of cultural attributes for product design. In this study, we investigate the contribution of integrating user requirements and cultural attributes for supporting designers in terms of designing cultural oriented product design. Furthermore, we will show our investigation into Vietnamese cultural aspects for product development. We will present a framework for culture-oriented product design, which is the combination of AI tools using big data, along with the process of brainstorming using cultural factors. We also do a case study of Vietnamese products.

User requirements play a significant contribution to designers in the early phase of product design. It would help designer understanding requirements for making a better product which satisfies the demand for market. The research aims at providing a framework for collecting user requirements from online user opinions.

1.5 Outline of The Thesis

This dissertation is organized as follows. Chapter 2 surveys previous work and research background on the user's requirements and introduces our framework for automatically obtaining user requirements from the online web. Chapter 3 shows the use of big-data we collected from a large scale of amazon online shopping data set to make it easy for showing to designers in product design. The interface would show designers about the set of review documents with the category, including helpful review, the number of ratings, and whether or not the online comment is positive, negative, or neutral. After that, we analyze how helpful reviews can contribute to product design. Chapter 4 describes the way how we can integrate the proposed model for improving product during a process. In this chapter, a framework for extracting online review documents are presented. First, we investigate appropriate techniques for extracting user requirements in online review documents. Second, the presentation of opinion summarization, as well as the use of top reviewer's information, is drawn in the chapter. Finally, the method of classifying review documents into either positive and negative is also discussed. In this chapter, we will present some cases study of exploiting the model in some kinds of products. Chapter 5 presents another study in our work that focuses on the cultural attributes to show that it is an important issue for product design. We investigate some case studies in culture-oriented products in which cultural attributes are taken into account for designers.

Finally, chapter 6 summarizes our contributions and draws future works.

Figure 1.1 shows the relation between each main chapter in the thesis. We can see the overview and the contribution of each part in the thesis.

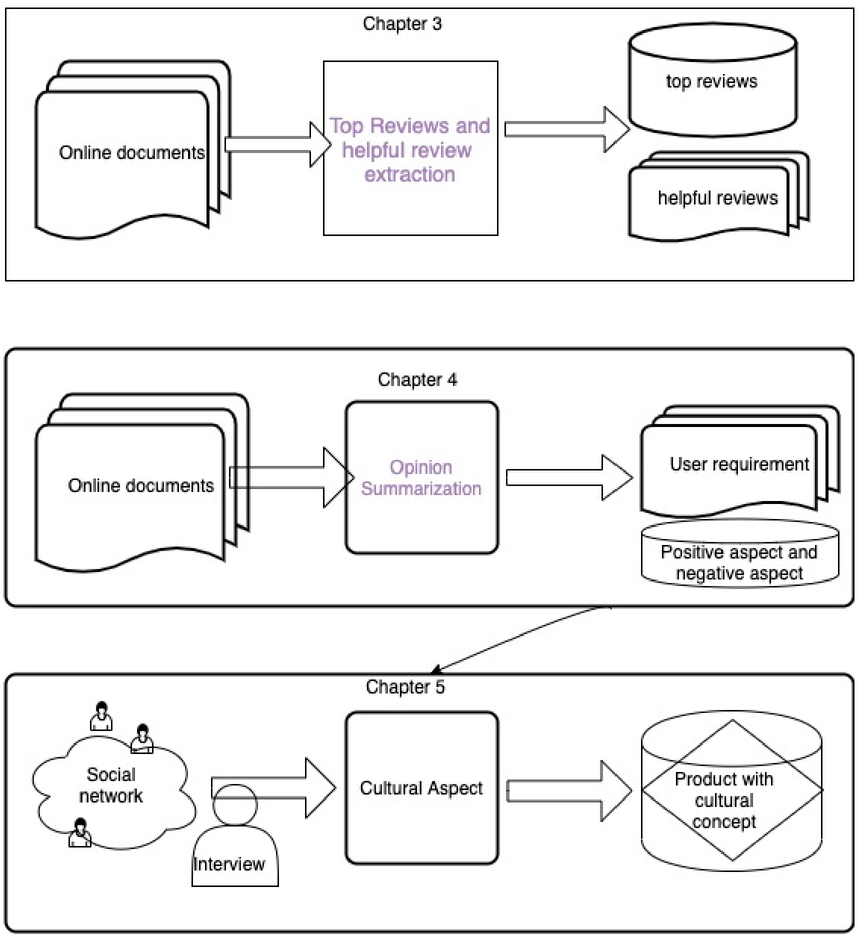


Figure 1.1: Overview of all main parts in our thesis

Chapter 2

Product Design and User Requirements

Product design plays an important role in business development. The definition of product design can be expressed as follows "Product design is conceiving and giving form to goods and services that address needs.". Product design process is the set of strategic and tactical activities, from idea generation to commercialization, used to create a product design. In a systematic approach, product designers conceptualize and evaluate ideas, turning them into tangible inventions and products.

Understanding people's needs for a given product or situation has become necessary to improve the quality of products and developments of the company or organizations. Organizations have realized that they cannot only rely on designers, developers or experts to know how to design products and services that meet customer requirements (needs). The people who order and/or pay for the product can be called customers. The people who interact with the product can be called users. The consumers are person who use the products. Research in product design has indicated that user involvement playing an important role in the product development. User involvement typically describes direct contact with users. It can be considered as the process of users participate, or integrate in the design or evaluate and implementation of new products. Normally, users often express their concerns or requirements when they interact with products. The challenge is how users needs (requirements) are collected for supporting designers in product design.

In this chapter, we will highlight the methods of capturing users requirements in product design, for supporting designers. First, we will show the background on user requirements and product design. Second, we will present traditional methods on capturing user requirement.

2.1 Product Design

Product design plays an important role in product development. The definition of product design can be expressed as follows: "Designing a new product goes through an analytical process and relies on a problem-solving approach to improve the quality of life of the end user and his or her interaction with the environment. It is about problem-solving, about visualizing the needs of the user and bringing a solution."

Product designers also work with other professionals such as engineers and marketers with a primary interest in usability.

Product design process is the set of strategic and tactical activities, from idea generation to commercialization, used to create a product design. In a systematic approach, product designers conceptualize and evaluate ideas, turning them into tangible inventions and products.

Figure 2.1 depicts the product design process which includes four parts: Idea generation and screening, concept development and evaluation, technical implication, and manufacturing and commercialisation.

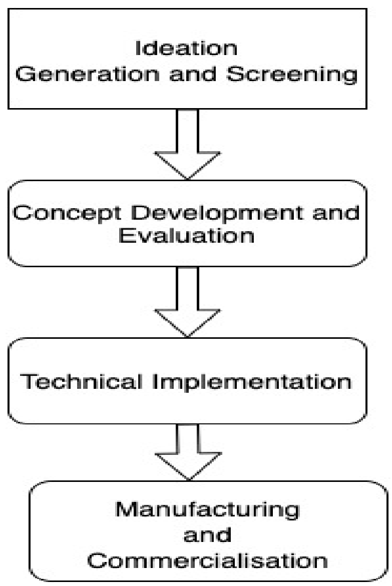


Figure 2.1: The Product Design Process

2.1.1 Idea generation and screening

The idea generation is often considered as a creative task (it may based on user requirements) [15][14]. It also can be treated as a problem of engineering design. Creativity techniques consists of the following

- Visual imagery of customers using existing products
- Using related product categories as idea's source (for example analogical thinking).

It is noticed that product design approaches typically consider the process of defining concepts is an important issue. It usually refers to finding (i.e using genetic algorithms) a subset of possible attributes[46].

2.1.2 Concept development and evaluation

The most popular methods to identify the ideal product include conjoint and other attributed-based models. It considers product design to be a convergence problem solving task that has a concept defined for a set of possible features or attributes. To find a combination of features as the best possible solution from a set of perspective, is very challenging task. It is also noticed that we can use modular architectures [72] for improve a product design process. The uses of modular architectures can lead to greater product variety, low time-to-market, and reduce the expensive of creating new product designs.

2.1.3 Technical implementation and manufacturing

One of the most researched concepts in product design is sharing parts, components, platforms, processes or resources on a family product. Using modular architecture techniques to create shared product platforms, components, and subsystems across a family of products allows a company to invest better leverage in design and product development [42]. Krishnan and Gupta point out that platforms are not suitable, however, for the level of market diversity or the high level of non-platform economies. One of the more noteworthy research trends is a focus on mass customization. Focusing on mass customization is the one of the important research trends in product design.

Researchers have also begun to address growing concerns about the sustainability attributes of products, where sustainability refers to meeting the needs of the present without compromising the ability of future generations to meet their own needs (UN Bruntland Commission, 1987), consistent with the philosophy of Design for Environment.

2.2 User Requirements and Product Design

2.2.1 User Requirements

User requirements(Needs) are not specific to the concept pursuing. It does not dependent on particular product we might develop. Customer needs should be identified without knowing if or how it will eventually address those needs.

Beside, specifications depends on how the concept can be selected. The "need" means to label any attribute of a potential product that is desired by the customer; Customer needs include customer attributes and customer requirements or user requirements. In this work, I focus on user requirements and explore the role of it in product design. On the other hand, regarding the customer attribute,we consider the cultural aspect in customer attributes.

2.2.2 The Need for User Requirements

The ultimate goal of identifying user requirements aims at creating a quality information channel directly running between the customer (user) in the target market and the developer of the product. This idea is based on the premise that people who directly control the product's details, such as engineers and designers, must interact with customers and experience the product's user environment. If there is no direct experience, technical trade-offs are not likely to be made precisely. Innovative solutions to user requirements may never get discovered, and the development team can never grow a deep commitment to meet customer needs.

User requirement is an integral part of the larger product development process. It is most closely related to concept generation, concept selection, competitive benchmarking, and product establishment specification. Customers' needs can be seen as the first step in new product design process.

Figure 2.2 demonstrates that needs playing both role product marketing and new product development. As indicated in the work[41], Step 1 shows thee recognition of a particular need. Note that many customers may be quite familiar with their own requirements and not familiar with technical specifications for selecting among competing products. Step 2 showed that the expressed by needs (voice of the consumer) can be translated into the language of the producer which is represented by product attributes. Once needs can be translated to attributes. The transitions from research to evaluation can be shown in Step 3. It answers a question which product (bundle of attributes) will best satisfy a particular need. Step 4 indicates the purchase decision.

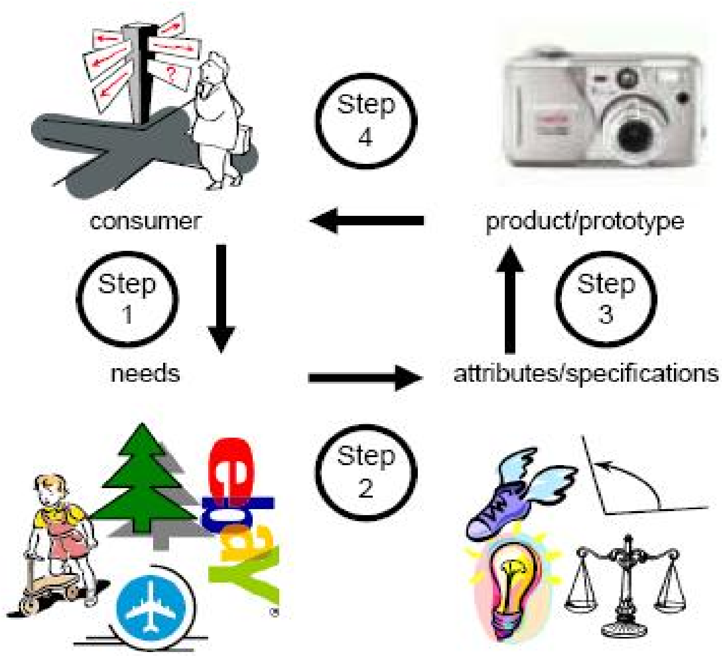


Figure 2.2: The Framework of Extracting Users Requirements

2.2.3 Factor that cause User Requirements

User requirements (UR) is generally the one of the main factor within user experience. User experience (UE) in a product-user interaction is a large and complex field. Figure 2.3 shows that field. It depicts the aspects that influence on interaction and UE to obtain URs. Intuitively, we can see that emotions and prior experiences are several influence aspects of users. An UE can be influenced by several aspects of product. Note that the aspects of a product will depend on the type of product and we can consider any kind of product. Let us consider an example as follows. Typically, in a "mobile phone" - the "desktop device" will have less emphasis than the "size" and "weight". The "context of use" is important and it can be varying a lot (i.e the customer will experience the use of product in different way in a public and private context). In addition, social and cultural factors will affect how the product can be interacted with the user and product and how he/she will experience its use.

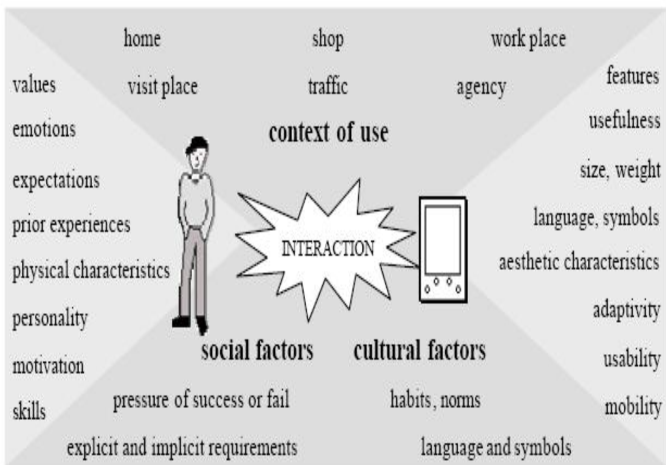


Figure 2.3: User requirement role in Product Development [48]

2.2.4 User Requirements in Product Design

In this subsection, a relationship between users requirements and product design process is presented. First, a product design is a procedure that specifies the means by which the product will provide the desired function. For product function, the design procedure often leads to the introduction of products without meeting user requirements.

During the design procedure, user requirement should be transformed into the required product by the designer. The design procedure represents the transformation of user (customer) requirement to a specification from which one can adapt the product. Designers highlight certain aspects associated with this specific user requirement (i.e complaint problem) in the transformation process. The design is seen to be related with the domain of problem-solving. Unfortunately, product design corresponding to customer requirement does not feel adequately solved for a cause of problem. As indicated, users want a appropriate product to satisfy intended requirements (needs). An appropriate product can execute its intended functions without any problem.

Figure 2.4 showed that the identification of user needs is the first step for defining a development plan in the product development process. General speaking, it is a very important step for product design. The teams can use the results of customer needs for establishing product specification. They also can apply for generating product concepts and selecting a product concept for further development.

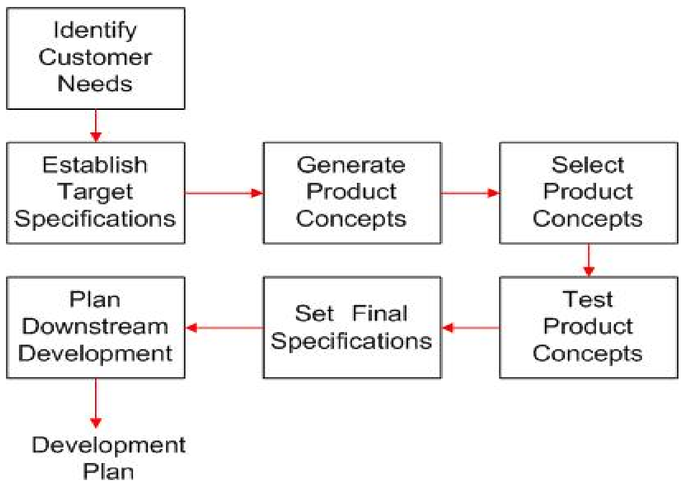


Figure 2.4: Customer Needs in Product Development

Note that, the relationship between user satisfaction and product design is tight. Typically, user satisfaction dependents on how a product is designed. Moreover, a product design is considered to be a collection of design features and their relationships. The design features are defined as the collection of human interface elements that the users see, hear, touch, or operate [26]. A specific design feature and the product as a whole affect user satisfaction. We can see an example When designing mobile phone as follows

- For mobile phone, its color may affect perceived luxuriousness,
- For the display, its arrangement and its relevant buttons may affect perceived harmoniousness.

An important issue is that identifying the design features of a product starts with determining the components and properties important to user satisfaction. To identify them systematically, Han et al. (2004)[25] assumed that a product consists of both hardware (physical) and software (logical) components.

For designing product, each component may have different properties. The properties were classified into three groups: individual, integration, and interaction.

For mobile phones we can divide into the following categories:

- size of button belongs the individual group.

- clearness of selected menu item belongs to integration group
- text input mechanism belongs to interaction group.

2.3 Methods for Capturing Users Requirements

Usability and design professionals know that URs gathering is critical to the quality product development. Previous works on collecting user requirements focused on interacting directly with customers using interview and questioners.

When designing product related to user requirements, the current research should define what user requirement is and how we can apply for designing product.

These methods consists of inspection, participatory design, workshops, photographs, stories, surveys, card sorting, cognitive walkthroughs, and story-boarding (Rohn et al. 2002). With that in mind, we would like to know the question about "what are the most suitable ways to capture information of user during or after using the product"?

In this section, traditional methods on capturing users requirements are discussed.

2.3.1 Process of Capturing Users Requirements

Capturing user requirements is itself a process, and it consists of five-step method as follows.

- Raw data from customers are collected.
- The raw data is interpreted with respect to customer needs
- The needs is classified into a hierarchy of primary, secondary, and (if necessary) tertiary needs.
- The relative importance of the needs are estimated
- The results and the process are reflected.

2.3.2 Gather raw data from customer

Interview and observation

Note that, the context of use will be emphasized in the case of gathering information of interaction between product and user. Therefore, interviews and observations should be made in the natural context of use. In addition, preliminary interviews and follow-up questions should be desirably carried out for gathering more information about user feeling of product and its use [1]. The interview approach can be viewed based on some sub-approaches as follows.

- Contextual inquiry is applied in the particular context of use for obtaining information of users. It typically uses in early phase of product development. It supports for improving existing product or developing a new product. It is important to note that observing users in real work situation is the main purpose of the method. Semi-structured questions about work should be made before stating the process and more questions could be asked after the working period[4].

- Ethnographic interview is an appropriate method for collecting information of users. The interview would focus on understanding user's daily life by interviewing at non-professional environment (i.e user home). The aim of interviewer is to know the work of users and vocabulary more comprehensively. It supports for observing the user in the contextual working environment.

The interview is considered as a suitable way for gathering information regrading interaction experience. This was because user can express how they feel about using the product. However, there is a limitation that in some situations users can not understand the guide of interviewer correctly, and something special information can be occurred without notification. Moreover, it is also difficult for user to tell how they experience certain features of product. Therefore, this method should be not sufficient solely.

The observation can also be utilized when gathering user requirements. However, this method requires knowledge about cognitive science that user's emotions and facial expression can be interpreted correctly.

Griffin and Hausers investigated the problem of how many customers for interviewing to know what is the most number of the revelation of customer needs.

- They indicated that with 30 interviews, the percent of the revelation of customer needs for picnic coolers is 90%.

- They estimated that the revelation of the customer needs for a piece of office equipment is 98% after 25 hours of data collection in both groups and interviews.

An important factor is that we can identify the users needs more efficiently by interviewing a level of customers called "lead/top users". The "lead users" is defined as the class of customers who experience needs long time ahead of the majority of the market and stand to benefit substantially from product innovations [80]. However, keep in mind that it is very difficult to approach to "lead users".

Scenarios and stories

Scenarios and stories can be considered as effective methods for gathering information of users including user's talk, an interaction with product, and the context of use. Interviewing or observing user is normally used with Scenarios. In addition, the user can be asked for writing scenario diary of their work which is useful in early phase of product design and development (Nikkanen 2001).

Stories can be considered as a good way for collecting information about interaction between user and product. This was because stories can be considered as natural way for communicating experience with other people [22]. Thus, users can explain how they experienced the use of product with product designers. In other aspect, scenarios can be used in product design.

Prototypes and Experience Prototyping

Prototypes is typically applied for to model a product being developed. The prototype of product can be used for The visualizing method to a user and designers a potential kind of the product (Leena 2003).

It is useful to perform prototype tests, for example, when working with prototypes, designers should define what kind of questions they want to find answers. Prototypes can be designed with respect to different purposes as follows

- Houde and Hill propose a model what prototypes prototype. It consists of three aspects of into analyzing prototypes: the role, the look and feel, and implementation [31].

- In addition to the traditional prototyping, Buchenau and Suri [6] have been presented experience prototyping (EP) which is able to simulating experience in different situations. EP can allow designers, clients or users to experience it themselves instead of just witnessing a demonstration or some else experience. In turn, designer can utilize that knowledge of experience for discovering new ideas to product as well as finding important factors for design process.

  More importantly, designers will get that experience in early phase of product development, which will save time and costs. EP enables designers, users and clients to get the first touch of existing or future conditions. In addition, product designers are able to get benefits by following activities: understanding existing experience, exploring design ideas and communicating design concepts.

Normally, we can inform design process and design decision by developing prototypes. Note that prototyping can be considered as an important activity in the interaction systems design [6].

Paper-based and voice-mail diary

Diaries is typically a good way for gathering information about interaction between a product and user. User's activities are written on a paper diary which can be unstructured or highly structured or unstructured. One of the limitation of this method is that user should write diary daily without doing any activity. Palen and Salzman (2002) [63] present an extended way to utilize diary studies using voice-mail diary method, which free the human using a pen and paper. The context for using this method can also be referred to the case when we gather information about user experiences in product interaction.

2.3.3 Interpret raw data in term of Customer Needs

Customer needs are expressed as written statements. The written statements are the results of integrating the need underlaying the raw data collected from the customers. Each statement or observation can be translated into any number of customer needs. We can list two main points for interpreting raw data in term of customer needs as follow.

- Expressing the need corresponding to what the product has to do (it avoids in terms of how it might do it). Customer preferences often expressed by describing a solution concept or an implementation approach; however, the need statement should be expressed regarding to independent of a particular technological solution.
- Expressing the need as specifically as the raw data.
- Using phrasing, positive, not negative.
- An attribute of the product can be expressed as the need. Wording needs as statements about the product ensures consistency and facilitates subsequent translation into product specifications.

2.3.4 Organize the Needs into a Hierarchy

It is difficult for dealing with the case when a large number of needs (requirements) is collected. Organizing the needs into a hierarchical list is typically an appropriate way. The list will typically consist of a set of primary needs, each one of which will be further characterized by a set of secondary needs.

2.3.5 Establish the Relative Importance of the Needs

It is essential for Designers to know relative importance of the needs in term of designing product. The relative important of the needs can be measured as a numerical important weighting for a subset of the needs. Typically, Designer can determine this value by theirs experience or basing the importance assessment on further customer survey.

2.3.6 Reflect on the Results and The Process

The final step in the method is to reflect on the results. The process of identifying customer needs can be usefully structured. The design team should challenge its results for verifying that they are consistent with the knowledge and intuition of which they have developed through many hours of interaction with customers.

2.4 The Relationship of User Requirements and Online Product's reviews

2.4.1 Limitations of These Methods

One of the limitations for these methods is how to approach users (customer). Choosing appropriate customers for collecting users need is very complicated process. Especially, it becomes more difficult when designing products that need interview a lot of users.

On the other hand, all the methods is time consuming and expensive. First, it takes time for either choosing customers for interviewing and gathering raw data from customers and processing the data for designers. This was because all processes are conducted in manually. Using such traditional methods, it is difficult to gather user requirements for a lot of diffident types of users. In addition, it is difficult to obtain a large number of users' information by using traditional methods because we can only access to a limited number of users. Furthermore, sometimes we cannot get their real emotions.

2.4.2 User Requirements and Product's Review

Along with the development of World Wide Web, number of users share their experience when using a certain product is increasing rapidly. We can see a lot of web-sites where they contain a million of users often sharing their experience such as Amazon.com, Ebay.com, and Epinion.

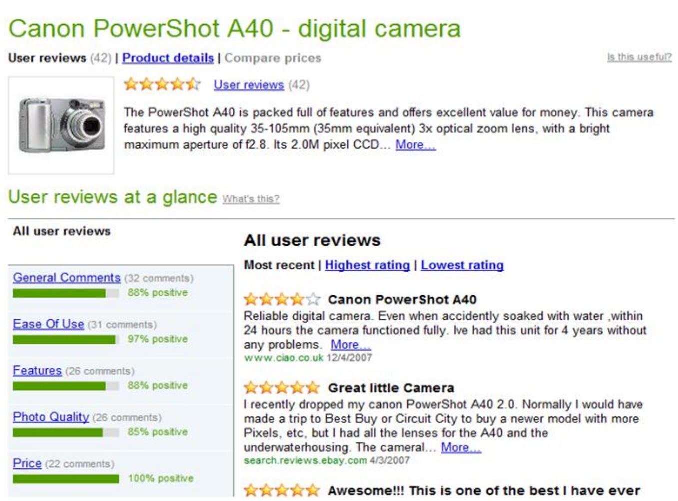


Figure 2.5: An Example of Product's Review for Cannon's Camera

[75][85].

Figure 2.5 shows an example of online review documents on the Cannon's camera. In this output, picture quality and (camera) size are the product features. It indicates that the total number of positive opinions about picture quality is 253 reviews while only six with negative reviews.

Interestingly, these web-sites itself contain a various kinds of users which come from many difference countries and their opinions about using the product reflect for their needs and their complains about the characteristic of the product. They also sometime compare the characteristic of the given product to other products of other manufactures. These information clearly reflect the users requirements. The hope of designing products is that we can satisfy as much as possible the needs of users. But, we need to know these information at first. These information are easily obtained from these web-sites mentioned above. However, to determine which sentences is the user requirements from a lot of sentence within a review document are not trivial work. Fortunately, there are a lot of works on processing Product's Reviews that we can utilize to extract user's requirements[34]

On the other aspect, online product's review contains a lot of opinion from users who have been used the given product. The reviewers have commented the characteristics of the products in which the positive and negative information are provided. In addition, the reviewers may compare the characteristics of the products with others. These information are very helpful for manufactures and it somehow is regard as users requirements of the product in that we do not take consuming time to identify needs by observing and interacting with customers through interviews, focus groups, and post-sales product registrations, rebates, and satisfaction surveys [41], [77]. The emergence of widely-accessible, freely-available, online reviews offers an opportunity to complement existing focus group and survey analysis with data from online reviews. Product's online reviews somehow convey a lot of information which mainly concern the opinion of users about the aspects of the product and it can be considered the requirements of users for that product. For example, young users would hope the shape of "mobile phone" to be dynamically suitable with their activities (i.e in office, shopping, in party). Those information are availability obtained on the web such as Amazon, Epinion, and Ebay.

There are some attempts to use an automatically method for processing user's needs for a limitation of product design. Urban and Hauser [78] propose to gather user needs by mining user transactions and interactive chat logs from the system named AutoChoiceAdvisor.

In the next chapter, I will propose a method for using opinion mining to support designers in the design process

2.5 Cultural Aspect and Product Design

The user requirements can be different from country to country due to the different of culture. Design studies have shown that cultural aspects can be seen as important factors for developing products from country to country. Culture, design, and their interaction make for an exciting research topic in this globalized world. Users are increasingly looking for differentiation in the products they own, as shown by [17] [62]. In this study, we investigate the contribution of a cultural dimension in product design. In addition, we discuss the relationship between culture and design, culture and the designer, and culture and the user. We also address different strategies for incorporating culture into design and the design process while designing for different cultures. For the sake of completeness, a brief overview of other research in the area of culture and design is laid out in this paper.

2.5.1 Design for different cultures

Culture-centered design

Culture-centered design (CCD), as shown in [74], results in the development of a design-based system. The main component of the CCD process is the use of metaphor and the two cultural filters at the designer and user levels, which get the designers and users views of the product interface. With the support of these two filters, the designer can compare their view of the product interface with that of the user. Then, the designer can improve usability and help convey cultural identity in the design. The designs could further be improved by applying local metaphors and representations. For this, background knowledge of the target user group and its culture, and considerations of its cultural filters (language, logic, and taboos), are essential for the anticipation of user behavior. In CCD, the appropriate choice of metaphor and its consistent use are the keys to successful interaction through design.

Designer preceded approach

Another interesting approach is the designer preceded approach, or DPA [71]. Note that when a brand-new product has to be designed and launched in an international market (where the culture of the target user group is different from that of the product designers), DPA can provide a competitive gain for a higher market share. The process comprises two stages: in the first stage, industrial designers in the target market are approached as potential customers for the proposed products, and they are asked to sketch a design brief that is identical to the one given to designers in the source country. The results of this exercise are analyzed to obtain a more precise idea about the product. Once a selected number of ideas have been generated based on concepts described by designers from the target country, designers from the source country expand on the concepts and themes that have been discovered.

Kansei design for cross-cultural perspectives

One of the interesting methods for cross-cultural perspectives is called Kansei design [11]. This method was carried out to understand the cross-cultural perspectives toward Kansei (emotional/affective) design principles via the design of a mobile phone. Following Kansei engineering procedures, the Kansei needs of consumers from different cultural backgrounds preferred the formal features of a mobile phone to be used in the context of different cultural backgrounds and the relationship between Kansei words and formal features for different cultural backgrounds were collated. The information obtained was used as a reference for designing cross-cultural mobile phones and other closely related products. Effective use of this methodology depends on prior knowledge of Kansei engineering and its associated procedures to derive the consumers Kansei needs.

2.5.2 Layer of Culture and Design

The work described in [30] showed Hofstede's cultural dimensions theory which is considered as a framework for cross-cultural communication. It depicts the effects of the culture of a society on the values of its members. In addition, it shows how these values relevant with behavior, using a structure derived from factor analysis.

The content of the theory of cultural dimension can be sketched as follows.

- **Power distance index (PDI)**: is defined as "the extent to which less powerful members of an organization or institution (or family) accept and expect that the power is distributed unequally. . In this aspect, inequality and centralization of power focus on being perceived by less powerful people. Therefore, a high PDI indicates a well-defined and enforced distribution of power in society without any doubts or reason. The low PDI indicates a high degree of interrogation about power allocation as well as attempts to divide the power [30].

- **Individualism vs. collectivism (IDV)**: This index shows the "level of integration of individuals with collectives and communities". A highly individualized society often has a relatively loose level of attachment and an individual tends to only engage with his family. They focus more on the subject "I" than "we". In the meantime, collectivism represents a society with close relationships of integration between families and other institutions and groups. The team members have absolute loyalty and always support the other members in each dispute with other groups and associations.

  [30]

- **Uncertainty avoidance index (UAI)**: defined as the "level of social acceptance of ambiguity", when people accept or prevent something that is not expected, unclear and different in comparison with normal situation. A high UAI indicates the level of engagement of members in that community with norms of conduct, rules, guidelines and often believes in absolute truth or a common "right" in every aspect that everyone is aware of. Meanwhile, the low UAI index shows the openness and acceptance of conflicting and controversial opinions. Low UAI societies are often less regulation-oriented, they tend to let everything be free to grow and take risks.

  [30]

- **Masculinity vs. femininity (MAS)**:

  in this aspect, "masculinity" is defined as "a society's priority for success, material rewards and a definition of success based on individual material accomplishments. In contrast, feminism refers to the importance of cooperation, humility, attention to difficult individuals and the quality of life. Women in society are respected and show different values. In that society, they share humility and care for gender equality. In more masculine society, despite being focused and competitive, woman is often less important than men. In other words, they also recognize the gap between values between men and women. This aspect is taboo in male-dominated societies [30]

Table 2.1: A comparison of cultural dimension among countries: power distance (PD), Individualism (ID), long-term orientation (LTO), Masculinity(Mas), Uncertainty Avoidance (UA)

Country	PD	ID	Mas	UA	LTO
Vietnam	70	20	40	30	57
China	80	20	66	30	118
Japan	54	46	95	92	88
Thai	64	20	34	64	56
USA	40	91	62	46	26
Denmark	18	74	15	23	unk

- Long-term orientation vs. short-term orientation (LTO):

  This aspect describes the connection between the past and the present and future actions / difficulties. When the LTO is low, it indicates the short-term orientation of a society where traditions are treasured and consistency is valued. Meanwhile, societies with high LTOs often focus on long-term process, care about adaptation and pragmatic when solving problems. A poor country, if it keeps its short-term orientation, it will be difficult for economic development. Meanwhile, long-term orientation is usually more conducive to development.

  [30]

- **Indulgence vs. restraint (IND)**:

  This concept is a measure of happiness, whether or not self-satisfaction is simple. Self-satisfaction is defined as ”society's permission to freely satisfy the basic and natural needs of the person, such as enjoying life” freely. While the concept of ”self-restraint” expresses ”the control of society, by strict prejudices and norms, in the enjoyment of individuals”. A society that allows enjoyment often creates confidence for the individual that he or she manages his life and emotions, while society that emphasizes restraint believes that there are other factors, control their own lives and emotions[30].

Understanding the meaning of these dimensions mentioned above would be helpful for designers to design the product more familiar with the local cultural aspect. In the next section, we will show the Vietnamese cultural aspects and how we can utilize Vietnamese cultural aspects for product design.

2.6 Summary

In this chapter, I briefly present the definition of Product design and the component in Product Design. We also discuss users requirements and its role in product design. In addition, the framework of bridging users requirements to product design is discussed. I also describe the traditional methods on collecting user requirements by directly interacting with users. I then discuss that the main disadvantages of those methods are time consuming and expensive. Therefore, a method for processing online product's reviews is required. In addition, we introduce cultural attributes (aspect) and its contribution to product design and indicate how we can combine cultural aspect with user requirements for designers in product design.

Chapter 3

Extracting Top and Helpful Reviews for Product Design

3.1 Introduction

As stated in the previous chapter, understanding user requirements (URs) would be an important role in designing product in the early process [77]. Typically, we can apply traditional methods for capturing URs. However, the disadvantage of those methods are time consuming and expensive. In addition, it is unable to collect URs from large scale of customers. Fortunately, it is easily for collecting valuable feedback from users across the internet, by processing a products reviews through online shopping sites.

Extracting useful opinion texts for supporting business intelligence and users has been taken much attention in recently. Early work proposed in [34] indicated that we can use opinion mining techniques to extract product features automatically. It is also shown that opinion mining plays a significant role in business intelligence [54][70].

Other works showed in [89][39] demonstrated that we can use multiple opinion text summarization for obtaining more useful text segments in terms of usability. Addition to these works, researchers indicated that one can use online reviews in the product selection process in the product design [86]. Another work [35] demonstrated that big consumer opinion reviews can be utilized for product design. An interesting work described in [83] analysed the perspective of designers for helpful online reviews.

Conrad and Kim (2011) ([76]) developed an efficient method which captures customer preference trends to enrich new product design process.

Along with the research line, in this chapter we would like to study a method for extracting user requirements from online customer reviews. However, unlike other previous works we focus on some following issues:

- First, it is noted that more useful information has been enriched in online websites so that we need to adapt our techniques to deal with this issue. For example, the format of customer reviews in Amazon has been recently changed very much with the information about ”top” reviews. We can access to top review including top critical and top positive reviews. From the voting of online customers, we can know the ratio of how many votes saying that review is helpful. Therefore, in our research we aim at utilizing the structure of reviews to extract user requirements from the largest online shopping sites. In fact, we will present a simple method for collecting a list of top customer reviewers and extract user requirements from top reviews.

- The second motivation of our work is to consider helpful review which have been indicated that effected to the marketing process in the product management. The recent work published in [83] demonstrated that helpful reviews are important for product design in terms of designers perspective. However, this work only conducted with a small set of reviews. In our work, we will present a model for detecting whether or not a review is helpful. The helpfulness is an interesting point in the sense that which may influence to other users in term of evaluating product. More important, if we consider the top rank reviewer who has many helpful votes from other customers, we can easily that most reviews from the top rank reviewer are useful.

This chapter is organized as follows. The first section will present our framework, which consists of two main components. The first component is to extract top reviews, and the second component is to identify helpful customer reviews. The proposed framework is evaluated by comparing it with other works in the benchmark data to verify the performance of helpful review identification. After that, we conduct an evaluation process with the consulting of designers via an interview process.

3.2 User requirements extraction for product design

This section presents the proposed framework for supporting designers by extracting customer reviews in the online shopping websites. We begin by analysing the structure of customer reviews in the website, to see how we can utilize reviews for product design. In order to do that, we propose our framework with the important components as follows: helpful review identification, sentiment classification, and keyword extraction.

3.2.1 Customer Reviews on Amazon Website

In this thesis the proposal framework will only collect customer reviews in English. However, it can be be applicable for other languages. First, we will analyse the structure of a review written by an amazon customer to understand the structure of a review. Figure 3.1 depicts a customer review example of a user. It contains the sections about the questions and answers about the product. The following sections indicate customer reviews with rating and then top reviews. In addition, we can also know how many peoples vote "helpful" for the review based on a special signal (symbol).

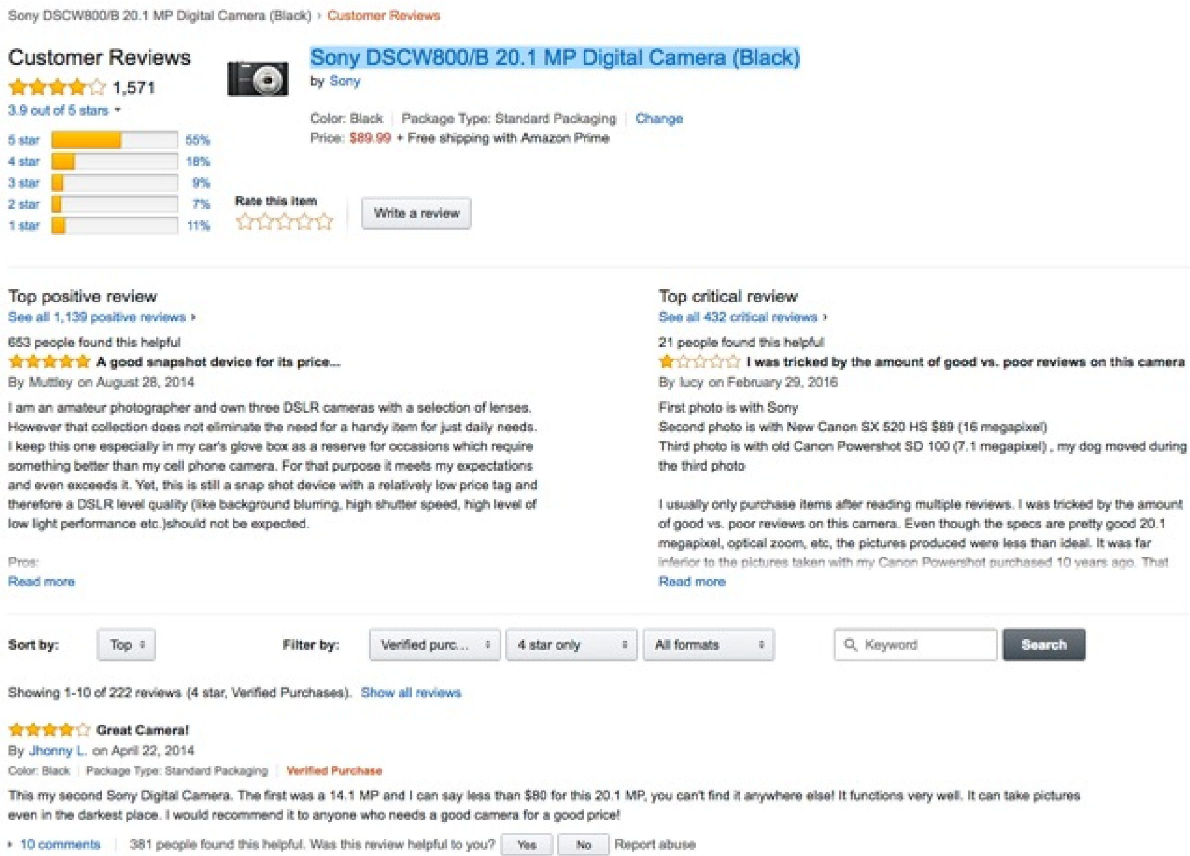


Figure 3.1: An example of customer reviews for Sony Camera collected from Amazon. The total reviews includes 1,139 positive reviews and 432 critical reviews. This example also shows the helpful reviews and the top customer reviews

On the Amazon website, we can also find a list of top reviewers rated by other customers by reading top reviews for given products. Top reviewers have many helpful reviews and they have had extensive experience with using the product. In turn, in product design, "lead users" are very important, so we might think that considering the top ratings in online sites as "lead users" in product design. .

3.2.2 The proposed framework: Extracting top and helpful reviews

This subsection will describe the proposed framework for extracting online customer reviews from the Amazon website.

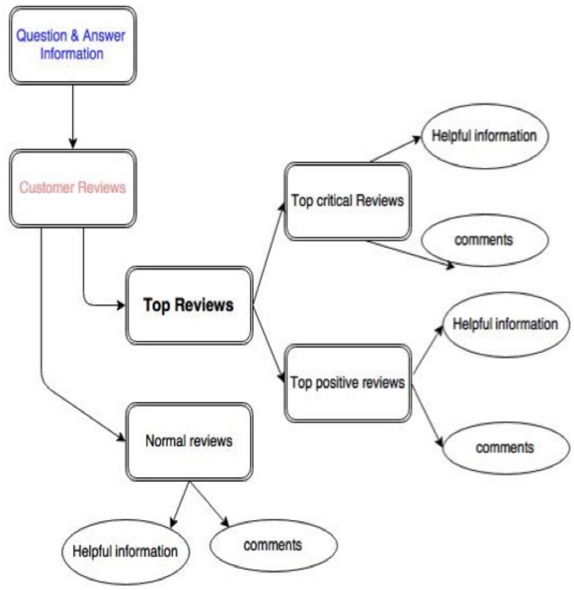


Figure 3.3: The structure of customer reviews for the product on amazon website.

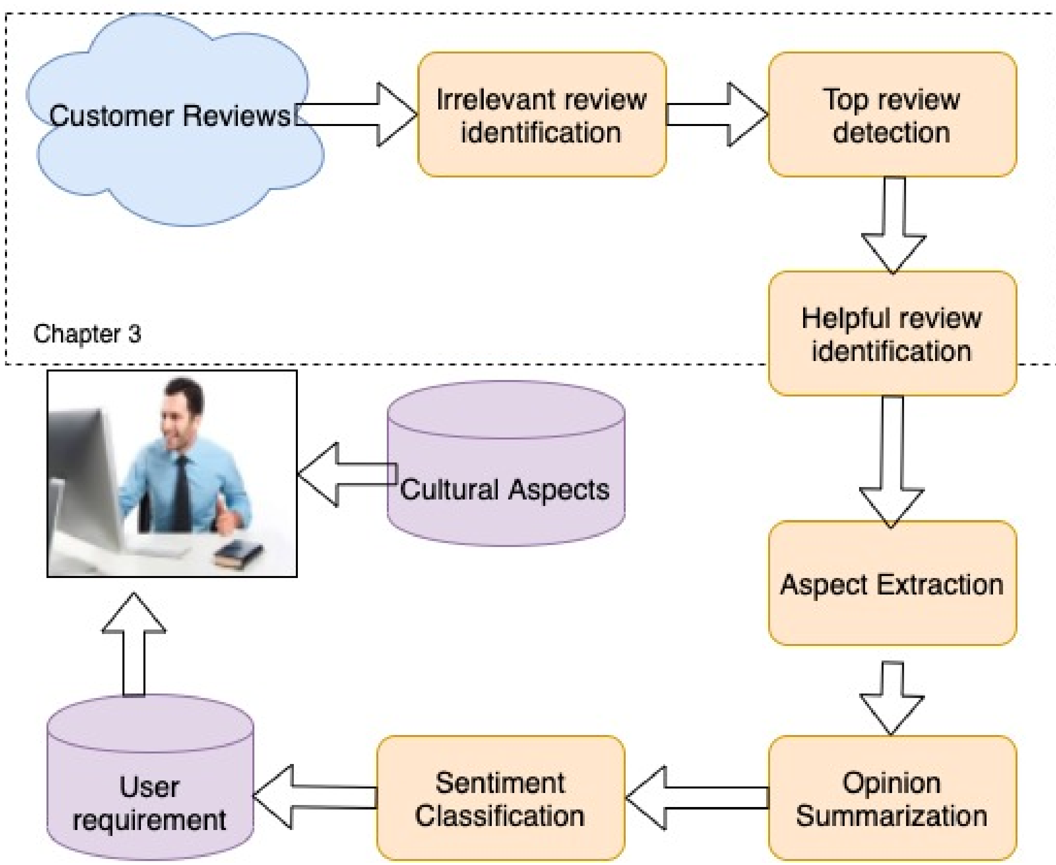


Figure 3.4: The proposed framework: user requirements extraction

Figure 3.4 depicts the framework for analyzing online reviews collecting from the amazon website. The process will be conducted using the following steps. In the first step, we crawl online reviews automatically from the websites. We then remove some duplicate reviews to obtain the customer reviews for our model. Some regular expressions can be used here to remove redundant customer reviews. For example, we can remove those reviews which have a short length. After cleaning reviews, a helpful review identification component is used for obtaining helpful reviews. After that, the top reviews and aspect extraction process will be applied for obtaining appropriate keywords and concepts for designing a product. The following procedure will summarize gist reviews corresponding with aspect (keyword), and each customer review will be classified into positive and negative categories. The final output is called user requirement, and the output will be provided to designers for the designing process. The collected reviews for a given product from the online shopping websites will be used as input for the proposed framework.

Preprocessing steps aims at removing stop word and performing word-stemming [65], are first exploited to the review documents for reducing noise. It is noticed that word-stemming is the process of reducing inflected or derived words to their stem, base, or root form. In our framework, we applied the suffix-stripping algorithm because it does not rely on a look-up table consisting of inflected forms and root form relations. In the suffix-stripping algorithm, rules are stored that provide a path for the algorithm to find a words root form, given an input word form. Given an input word form, we use a set of rules described in [40] for finding a word's root form.

Learning Model to Classify Irrelevant Reviews

This subsection will present our work on dealing with irrelevant reviews. We formulate this problem as learning to classify irrelevant review documents. To do that, we used the training data set described in [36] for our learning problem. Unlike the work described in [36], we investigate several machine learning and deep learning models to select appropriate methods. Moreover, we collected a set of reviews from experts, which are quality product reviews. Top reviewers are identified by collecting useful information in customer reviews. It is easy to see that we can use some signs in the presentation of the Amazon website for determining whether or not a review is a top positive review or top critical review.

Top Customer Reviews

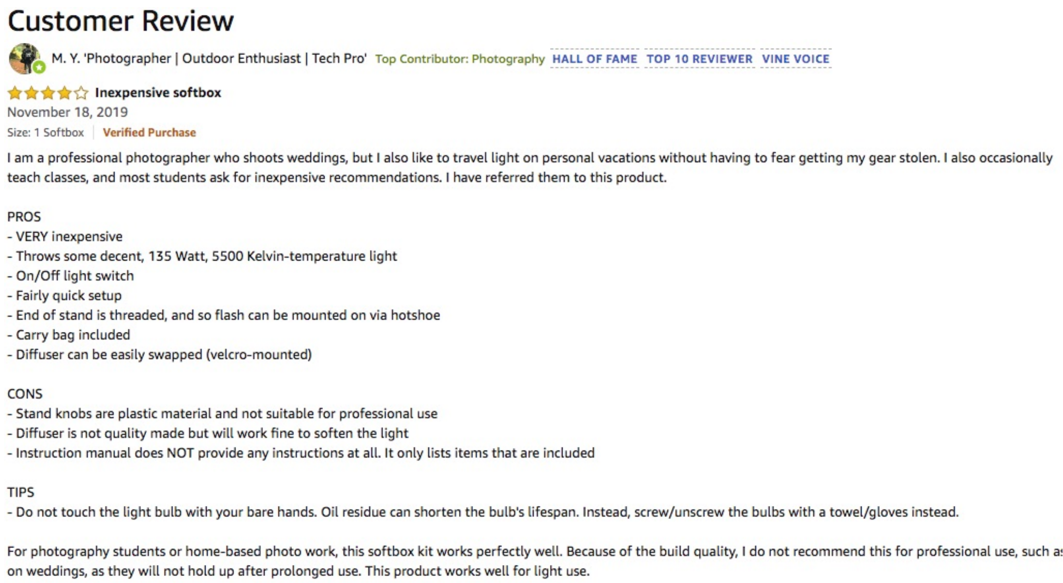
Top customer reviews are collected by applying a simple regular expression rule finding on a set of customer reviews. The regular expression will find those reviews with a tag <top review>. After observing the Amazon website, we found that top reviews often occur in the first place of customer reviews. Among top review, the top reviews are classified into top positive and top critical reviews. This was because the customer reviews on Amazon has some categories to detect whether it is the top review, so a regular expression method is applied for obtaining top customer reviews among all customer reviews related to the product. Another method is to obtain the list of top reviewers that are posted by the

Amazon website. Figure 3.1 shows the list of top customer reviewers we obtained. As can be seen, the top customer reviewers have displayed a lot of comments about the product, and most of their reviews are evaluated helpful by other customers. This means that the top reviewer can influence other customers very much.

Table 3.1: The Top Customer Reviewer List[1]

ID	total reviews	total helpful votes	percent helpful
[Hoppaguy]	2,034	13,161	97%
[Serenity.]	2,785	24,178	96%
[C Wm (Andy)]	2,532	45,611	96%
[Kate ***]	1,317	24,716	98%
[PhotoGraphics]	1,952	47,628	96%
[iiiireader]	4,678	58,216	97%

Table 3.1 depicts the top customer reviewer list which shows the reviewer name, the total reviews, total helpful votes, and percent helpful votes. Most the top reviewers have very high percent helpful and the number of helpful votes. Most top reviewers have more than 96% helpful votes among more than 1,300 reviews. In addition, they got quite big number of helpful votes. It is interesting to see a large number of top reviewers via internet. We manually read the top reviewer [Hoppaguy] in the first rank. Interestingly, we found that the first rank reviewers typically write a review a long with video and pictures of testing the product. This factor is also very important for the design process in product design. Looking at the top rank reviews, we found that he wrote very well organize reviews. The reviewers listed ”Pro” and ”Cons”, as well as the ”tip” and the use case of the product. Some reviews include images and videos to illustrate the use of the product.



Customer Review

M. Y. 'Photographer | Outdoor Enthusiast | Tech Pro' Top Contributor: Photography HALL OF FAME TOP 10 REVIEWER VINE VOICE

Inexpensive softbox

November 18, 2019

Size: 1 Softbox | Verified Purchase

I am a professional photographer who shoots weddings, but I also like to travel light on personal vacations without having to fear getting my gear stolen. I also occasionally teach classes, and most students ask for inexpensive recommendations. I have referred them to this product.

PROS
- VERY inexpensive
- Throws some decent, 135 Watt, 5500 Kelvin-temperature light
- On/Off light switch
- Fairly quick setup
- End of stand is threaded, and so flash can be mounted on via hotshoe
- Carry bag included
- Diffuser can be easily swapped (velcro-mounted)

CONS
- Stand knobs are plastic material and not suitable for professional use
- Diffuser is not quality made but will work fine to soften the light
- Instruction manual does NOT provide any instructions at all. It only lists items that are included

TIPS
- Do not touch the light bulb with your bare hands. Oil residue can shorten the bulb's lifespan. Instead, screw/unscrew the bulbs with a towel/gloves instead.

For photography students or home-based photo work, this softbox kit works perfectly well. Because of the build quality, I do not recommend this for professional use, such as on weddings, as they will not hold up after prolonged use. This product works well for light use.

Figure 3.5: A review of the top customer reviewer

Figure 3.5 shows an example of a review collected from the top customer reviewer. As can be seen, some top customer reviewers even provided the "pro" and "cons" of the product. Also, the top reviewers indicated the tips and cases for other customers. The structure of the top customer reviewers would be very easy for extracting user requirements.

Algorithm 1 shows a very simple method to extract user requirements from the top reviewer.

Algorithm 1 Algorithm for extracting user requirement from top reviewers

---

Collect the list of top customer reviews and store it in the dictionary
if *Reviewer belongs to the top list* **then**
  Obtain all reviewers by crawling from the amazon sites.
  Index all reviews
  Extract "pro" and "cons" of the reviews

end
if *normal review* **then**
  Extract helpful reviews
  Extract user requirements using keyword extraction
  Classify reviews into positive and negative

end

3.2.3 Helpful Review Identification

In this step, a helpful review identification model is developed. This component allows us to classify a review into two categories: helpful (positive) or non-helpful (negative). There are not so many works studying helpful reviews for designers. The most relevant to our work is presented in [83]. In this work, the authors investigated the use of linguistic features for review identification, which takes into account the perspective of designers. Unlike this work, we consider investigating both conventional machine learning models and deep learning models for our problems. The following machine learning models are investigated in our work, including:

- Support Vector Machine (SVM) and XGBoosting. These machine learning models are selected because they often achieve very good results.
- deep learning methods: We consider the following deep learning model which are Convolutional Neural Network (CNN), FastText models, and BERT models which often achieved the state of the art performance in text classification.

The training data for building our helpful identification model is obtained from the Amazon website. We then investigate several deep learning models including the CNN model, FastText, and BERT text classification.

Support Vector Machine with Linear Kernel

Support Vector Machine (SVM) with linear kernel has been widely used as baseline model for text classification problem as it is suitable for the vector space representation of text data. Such representation has the following properties [37]:

- High dimensional space: it is normal for the feature space to have hundreds to thousands of dimensions when using text representation techniques such as tf-idf.
- Representation vectors are usually sparse: most of the values are usually zeros as with tf-idf term weighting scheme.
- Text classification problems are often linear separable

In this study, we use SVM with linear kernel and the traditional feature extraction techniques, e.g. tf-idf or topic modeling, as the baseline for comparison with deep learning and other models.

XGBoost

Tree boosting has been proven to be a strong learning algorithm for many NLP competitions on Kaggle. Among different algorithms, XGBoost is a highly efficient, well optimized and flexible one.

We will compare the use of XGBoosting with other learning models for helpful identification problems.

Convolution Neural Network:CNN

The CNN model is originally developed for text classification and achieved very good performance [88]. The advantage of using deep learning models is that we can learn feature representation from the data so that it can easily convert a sentence into a vector representation. Typically, a word embedding model can be used in the deep learning model. In our research, the Word2Vec model [33] is used to encode a word into a vector representation.

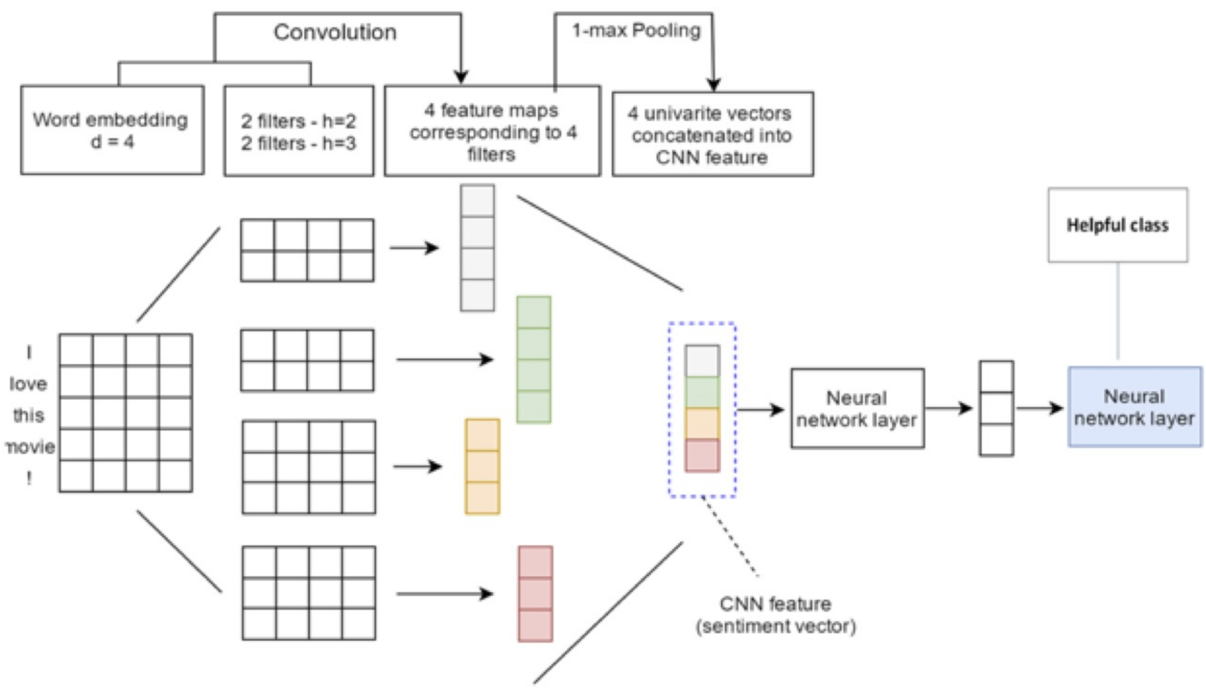


Figure 3.6: The CNN model for helpful review identification.

Figure 3.6 describes a CNN model for identifying helpful reviews. For convolutional layer, we used 4 filters with the window size is equal to 2 and 3, respectively. In addition, the max-pooling layer is used in the framework and the input vector is encoded with the Word2Vec model.

BERT

The pre-trained language model is designed for representing a context to words that have previously been learning from unannotated training data. Bidirectional encoder representations from the transformer model (BERT) is a pre-trained language model which can utilize the larger context representation of a word from both left and right side simultaneously [20][19]. This representation is applied for various natural language processing tasks with very high performance. We can typically design BERT for the helpful identification problem by using the fine-tuning technique. We utilize the BERT representation from large unlabeled data, then conduct a fine-turning on the helpful training data.

FastText

FastText is a tool for dealing with text representation and text classification. This method utilizes sub-word information by incorporating character n-gram into the skip-gram model, even though it is a simple model. Still, its computational time in training is very fast. Also, this method can learn without requiring any preprocessing or supervision. In the work described in [38], the authors pointed out that FastText improves the strong baseline models that do not consider sub-word information, as well as methods using morphological analysis. Facebook Research releases FastText as an open-source code [2]. This tool is widely applied to many text mining applications.

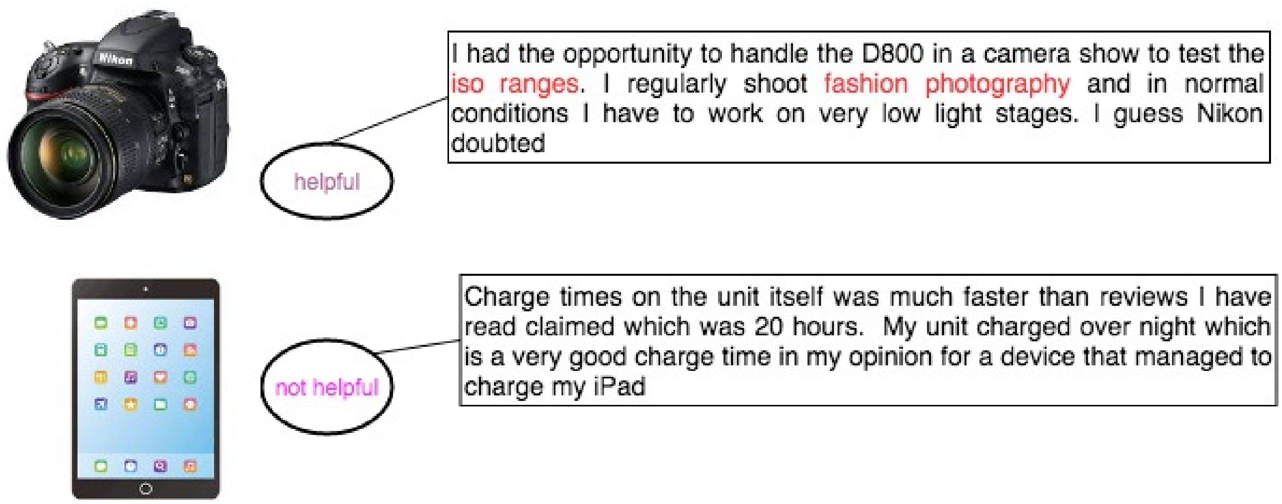


Figure 3.7: An example of helpful review and not helpful review

Figure 3.7 shows an example of a helpful review and non-helpful review predicted by our system. It showed that the "non-helpful" does not contain any useful information while the "helpful" highlights some useful information for users. Those helpful reviews will provide useful information for designers in terms of designing products.

3.3 Experimental Results

To verify the performance of the proposed framework, we will evaluate the accuracy of a helpful review classification with various machine learning models.

3.3.1 Helpful Review Identification

The training data for helpful review identification are collected from the amazon website which is made available via the specific address[3]. In our work, we focus on three categories:

[2] https://fasttext.cc/
[3] https://nijianmo.github.io/amazon/index.html

mobile phone, Fashion, and Electronic products. The statistical information about the data we selected for three categories, as shown in Table 3.2. To evaluate our framework, we split our data into 80% for training and 20% for testing, respectively (we randomly select the test data). After that, among 80% training data, we choose 20% data to be development set, which will be used for turning parameters.

Table 3.2: Statistical information about Amazon dataset

Cell-Phones (Cat1)	Fashion (Cat2)	Electronics (Cat3)
131, 267 helpful reviews	304,492 helpful reviews	699,012 helpful reviews
296,928 non-helpful reviews	435,411 non-helpful reviews	1,006,225 non-helpful reviews

We conduct our experiments to verify various machine learning models including: SVM, XGBoost, Fasttext, BERT, and CNN models. We also applied the bagging models with a voting mechanism to combine the three learning models (SVM, XGBoost, and Fasttext) and four models (SVM, XGBoost, Fasttext, and BERT). We denoted theses models are voting(3) and voting(4), respectively.

$$\text{Accuracy} = \frac{\text{total correct helpful prediction}}{\text{total of test samples}} \tag{3.1}$$

Table 3.3: Performance of helpful identification model

Methods	Cell-Phones	Fashion	Electronics
SVM	72.5	65.7	68.1
XGBoost	72.6	65.4	68.9
Fasttext	65.5	65.51	67.5
CNN	69.0	68.13	70.13
BERT	**69.8**	66.0	**69.4**
Voting (3)	69.8	66.0	**69.4**
Voting (4)	**72.8**	65.7	68.6

As indicated in Table 3.3, the CNN model obtained a higher result in terms of accuracy than that of the FastText. The BERT model achieved the best result in electronic data, and the ensemble model using the voting method achieved the best accuracy in the cell-phone data. The CNN model obtained the best result in fashion data.

We also conducted to verify the proposed framework in the second test data after manually removing some sentences including noisy sentences and those short reviews in both training and testing data. After having the new training and testing dataset, we did

Table 3.4: Performance of helpful identification model

Methods	Cell-Phones	Fashion	Electronics
SVM	65.1	71.9	77.4
XGBoost	67.8	69.5	76.4
Fasttext	71.5	70.2	74.2
BERT	**83.2**	85.9	**80.3**
Voting (3)	69.3	74.16	**75.9**
Voting (4)	**70.5**	70.5	72.6

a comparison among machine learning methods to evaluate their performance. The results showed that BERT attained the best performance in compassion with other models.

In general, the BERT text classification obtained the best result in two experiments. It is also claimed that BERT obtained the state of the art performance in many text classification tasks. Therefore, in the proposed system we choose BERT as the final model helpful reviews identification models.

3.4 Case Studies

In this section we would like to investigate the two hypothesis as follows:

- Hypothesis 1: In the first item, we want to verify how top reviews are important to designers when they want to use it for designing product
- Hypothesis 2: In the second question, we also want to ask the designers about helpful reviews and how it contribute to product design.

3.5 The Case Study I

We consider the top reviews and normal reviews for verifying which reviews are more useful for designers. We carry out an evaluation by designers to determine how helpful reviews contribute to product design with the laptop and camera.

We will consider the uses of Canon camera' s reviews and the Laptops reviews on the Amazon website. We indexed all customer reviews from the top reviews on the Amazon website to our system. Besides, we obtain all reviews on Fashion, Cell-phones, and Electronic to stored in our framework. After collecting reviews, our framework will be applied for extracting user requirements. For convenience, we provided 20 top reviews and 20 regular reviews for designers to read them before answering those questions in the questioners. The experiment will be conducted as follows. First, those customer reviews are selected using helpful categories among customer reviews. The helpful customer review identification model is applied for selecting helpful customer reviews.

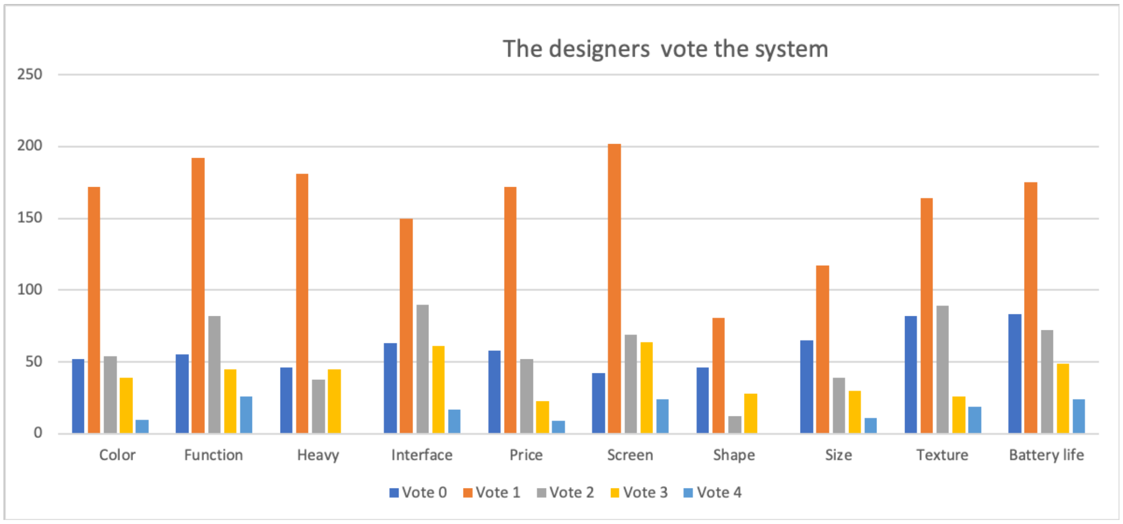


Figure 3.8: designer votes on helpful reviews obtained by performing the proposed system: a set of helpful reviews corresponding with each aspect

We interview designers using the questionnaires as shown in Appendix (see the Appendix). There peoples (the person who understand design knowledge) are asked to answer the questioners. The input of reviews and the outputs of the proposed systems are provided for designers and each designer has totally 50 minutes to conduct their task.

Because conducting an interviewing process is time-consuming and complicated, so we do an interview process with the designers to verify our framework. Interestingly, all designers agreed that the output of the proposed framework could save time for designers in terms of understanding users' requirements.

After asking designers about the top customer reviewers, we can see that the top reviewers have influenced the customers and designers very much. The top reviews contain more information than normal reviews. The top reviews typically have its structure, such as "Advantage" and "Disadvantage" which would support designers to understand user requirements quickly. Regarding top reviews, we also consider two types of reviews: top positive reviews and top critical reviews. According to designers, the top critical reviews seem to contain more useful information for the designers than top positive reviews. It is also interesting to know that those reviews with a higher helpful score would bring more helpful information for designers than those reviews with a lower score. The top keywords selected by designers are mainly relevant to the aspect function of the products. The reason is that the designers would focus on improving the camera's function and memory aspects of the laptop.

3.5.1 Ablation Test

We conduct an experiment by verifying whether the results of helpful review identification is essential to the designers. Figure 3.8 showed how people voted for a sentence being helpful or not helpful. We chose the sentence corresponding with 10 aspects (i.e color, screen, size, battery, weigh, etc).

The sentences are obtained the number of votes from 0 to 4 votes. After checking the output of the proposed system, we can find the issues as follows:

- a long review tends to be more helpful
- Helpful reviews tend to mention many product features trends
- There are not many online customer reviews mentioning many different products. A helpful review may only mention one or two similar products for preference comparison,
- Helpful reviews tend to mention both the advantages and disadvantages of products
- Reviews with higher helpful score would bring more useful information for designers than those reviews with lower helpful score.

The results showed that there are still some redundant reviews that are not selected by designers, so we may think of applying the opinion summarization component for removing them in the next chapter. Also, designers often consider helpful reviews in terms of some aspects. Therefore, extracting aspects are important issues, and they will be considered in the next chapter.

3.6 Summary

In this chapter, we have proposed a novel framework for extracting users customer reviews from online shopping sites to support designers in the early phase of the design process. The proposed method can identify helpful and top reviews, which showed promising results for product design. Experimental results on the standard data set showed that helpful review identification demonstrates a very promising result. We also verify the proposed system with designers to understand how the designer would choose a helpful sentence. We conduct an interview to compare the top reviews and regular reviews, as well as the importance of helpful reviews from the perspective of designers. In the future, we will investigate a method for dealing with different languages and consider cultural aspects of product design.

Chapter 4

User requirements for product design: A Supportive Framework

4.1 Introduction

The research line on extraction useful information from online customer has significantly taken into account by many researchers [34][54][70]. Their works showed that product features can be obtained automatically and play an important role for business intelligence. In addition, many research has showed the significant uses of opinion mining techniques for product design [89][86])[35]) [83])[76][39]. Along with the research direction, in this chapter we present a new framework with the motivations as follows.

- Unlike the works described in [89][39], we consider a framework that can allow the user interact with the system through queries, which are able to obtain a higher accuracy in the extraction process.
- We add a component that can classify extracted review sentences into the two categories positive (advantage) and negative(disadvantage). This will provide more information for designers for considering in their design process.
- Several multiple document summarization techniques are investigated to select appropriate methods for dealing with customer reviews.
- We evaluate the proposed method to assert the usefulness of interacting with designers. A case study with Nokia phone, electronic products, and fashion products are discussed in the chapter.

The contributions of the chapter include two main folds:

- A novel method for collecting review documents and extracting user requirements are discussed in the paper.
- We evaluate our framework in the standard data sets and verify with the case studies for product design.

The structure of this chapter is organized as follows. We begin with an introduction about the proposed framework in which we present aspect extraction, text-summarization techniques. After that we present a study on using sentiment classification for classifying online reviews into positive and negative categories. In order to evaluate the proposed framework, we verify it in the standard data and compare each component in the proposed framework with other works. Then, we exploit the proposed system to validate with designers. We also conduct an interview with designers to understand the contribution of the proposed framework in product design. Finally, we provide our conclusion and discuss our future works.

4.2 User requirement extraction

This section will show our framework for capturing user requirements. We first define what is user requirement in our work as follows. The user requirement is a set of aspects and its customer opinion about the aspect though which we can understand about the advantages and disadvantages of the product with respect to the aspect.

Figure 4.1 shows a list of URs after performing the proposed framework on the collection of reviews.

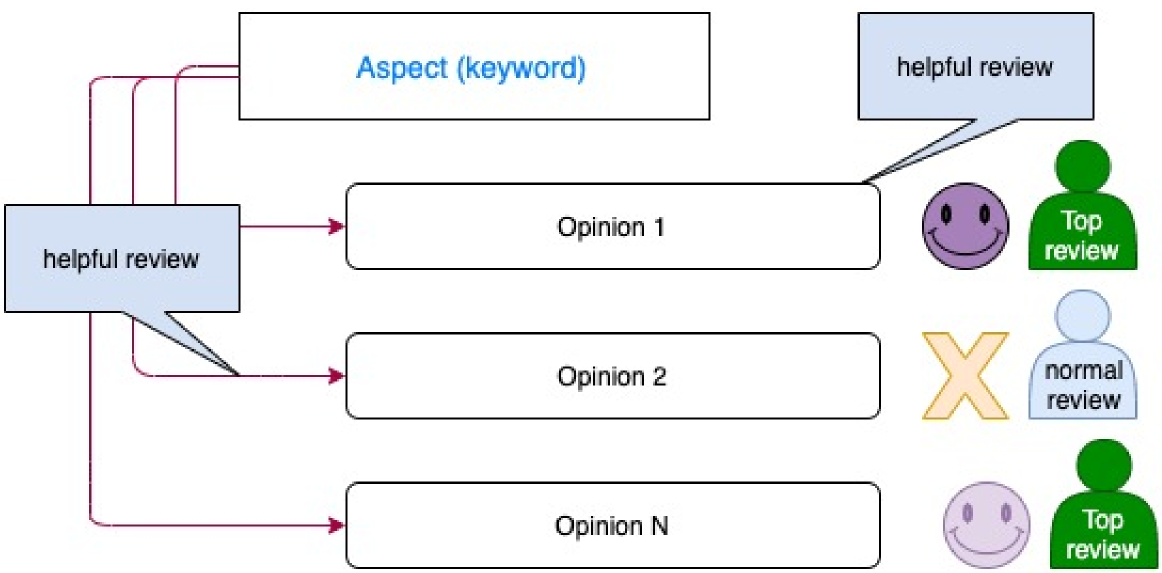


Figure 4.1: An example of user requirement on the aspect

To extract user requirement, in Chapter 3 we are able to verify whether or not a review is helpful or top review. In this chapter we want to find all aspects and its corresponding reviews to the aspect.

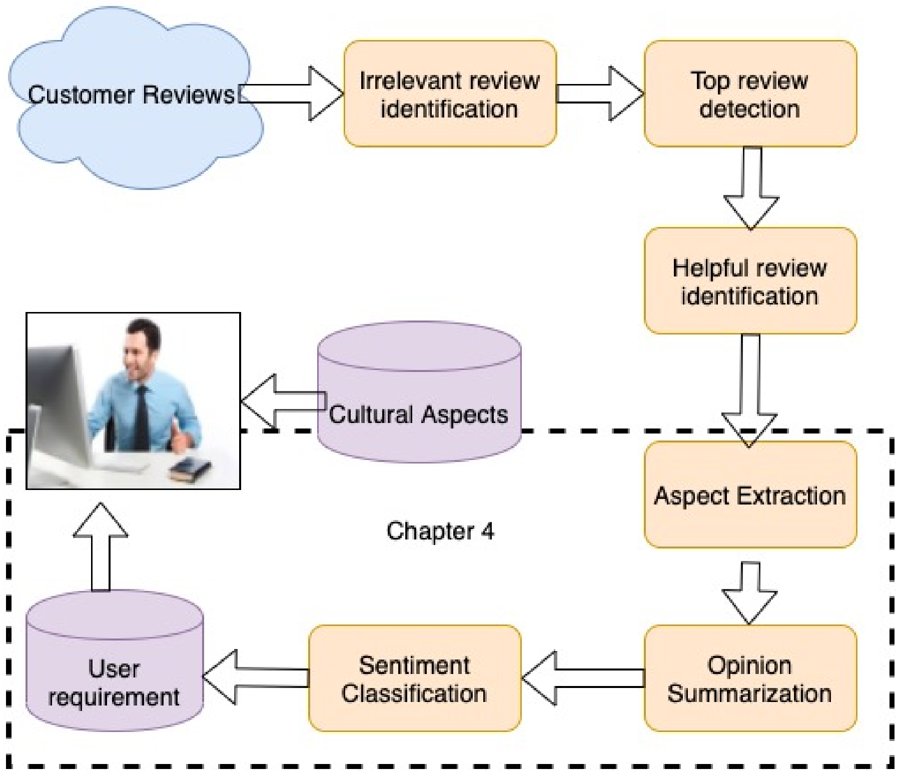


Figure 4.2: The proposed framework: user requirements extraction

Figure 4.2 depicts the framework for user requirement extractions from online customer reviews. After the process of top review and helpful review identification in Chapter 3, the framework will perform aspect extraction for obtaining appropriate keywords and concepts for designing product. The following process will summary main reviews which corresponding with aspect (keyword) and each review will be classified into positive and negative categories. The final output is called user requirement and the output will be provided to designers for designing process.

4.2.1 Aspect Extraction

This subsection will present the aspect extraction framework. The ultimate goal of our work is to collect useful information with respect to user's interest. There are two methods for aspect extraction including unsupervised learning methods and supervised learning methods. In our work, we will study the two approaches: unsupervised learning and supervised learning to choose appropriate methods for our work.

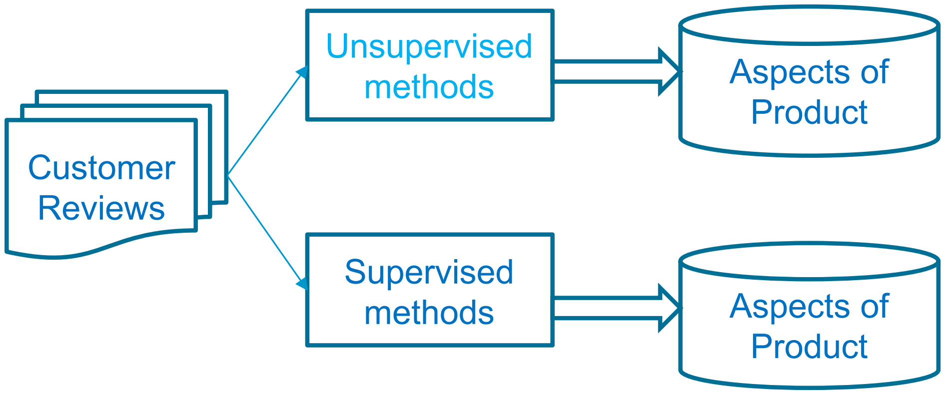


Figure 4.3: Aspect Extraction Approaches

Unsupervised Method: Keyword Extraction for Aspect features

The proposed framework consists of the product features extraction and the procedure of finding corresponding sentences mentioning these features in a set of customer reviews.

Greedy method: The first method [34]is applies a searching algorithm to find frequent nouns or noun compounds in opinion reviews. Another simple method [89] applies a simple algorithm for extracting all potential feature candidates. It considered all sequence occurring in the documents with a frequency being higher than a predefined value. In the first step, it collects all co-occurrence with the length 2. Then, it used the set of keywords with the length 2 to find all keywords with the length 3 and so on. Finally, a set of aspect features are selected by using a scoring method [89] to choose a top aspect features.
Sequence Mining method: Another method is to formulate a sequence as a transaction (a sequence of words), then applies a sequence mining technique to find a sub-sequence of words occurring frequently in review documents. The outputs of keyword extraction will be considered as candidates for aspect features.

In our work, We applied a sequence mining tool (prefixspan)[1] for generating a list of word sub-sequences and their frequency. The filters are exploited to this list for removing the noise keywords. For example, we eliminate potential phrases composed of stop words or candidates occurring with a low relative frequency. Let N, n, and l be the number of review documents, the reviews in which phrase appears, and the length of the phrase, respectively. Let f be the frequency of the phrase occurring in the review set. We can estimate the priority of the phrase (or feature) based on the score as follows:

$$\text{score} = f \times \log_2 \frac{N+1}{n} \times \log_2(l+2) \tag{4.1}$$

The features are ranked using the equation mentioned above then the top rank features are selected as the final list of feature sets. Table 4.1 demonstrates a list of features after performing keyword extraction techniques.

[1]http://chasen.org/ taku/software/prefixspan/

Table 4.1: Examples on features extraction of Ipod

Features	Frequency	Rank
Battery-life	11	1(61.87)
Web-browser	7	2(50.1895)
Music-videos	5	3(40)
MP3-player	4	4(35.183)
Safari-web-browser	3	5(33.487)
YouTube-application	3	6(28.84)
Album-artwork	3	7(28.84)

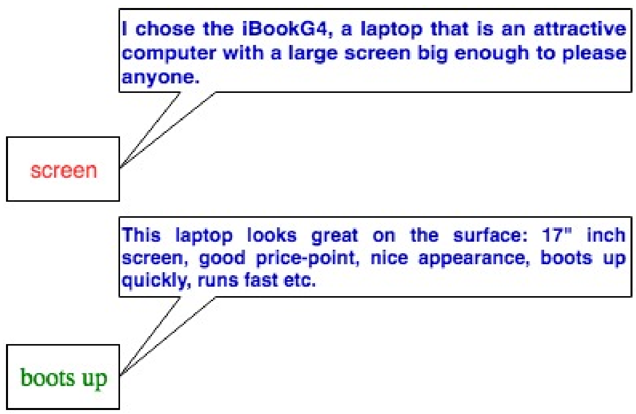


Figure 4.4: The illustration of the proposed system

In addition to the list of features generated by the system, we add some static features which are commonly used in the product. For example "screen" and "sharp", etc. We used the combination of static features and dynamic features by means of ensuring that all aspects within the product are considered. This would help to understand the opinions of reviews in more details.

Unsupervised method: Attention-based Aspect Extraction (ABAE)

With the power of deep learning model, we can exploit an attention-based aspect feature using neural approach as described in [28]. This method uses an unsupervised approach with an attention mechanism to extract all possible features without using training data. The results has been showed it outperformed other unsupervised approach on the benchmark data [28]. Note that, the sequence mining method can generate a large number of feature aspects than the deep learning-based approach, but its results contain more noisy features.

Figure 4.13 depicts two examples of using the method for extracting aspect from the sentence.

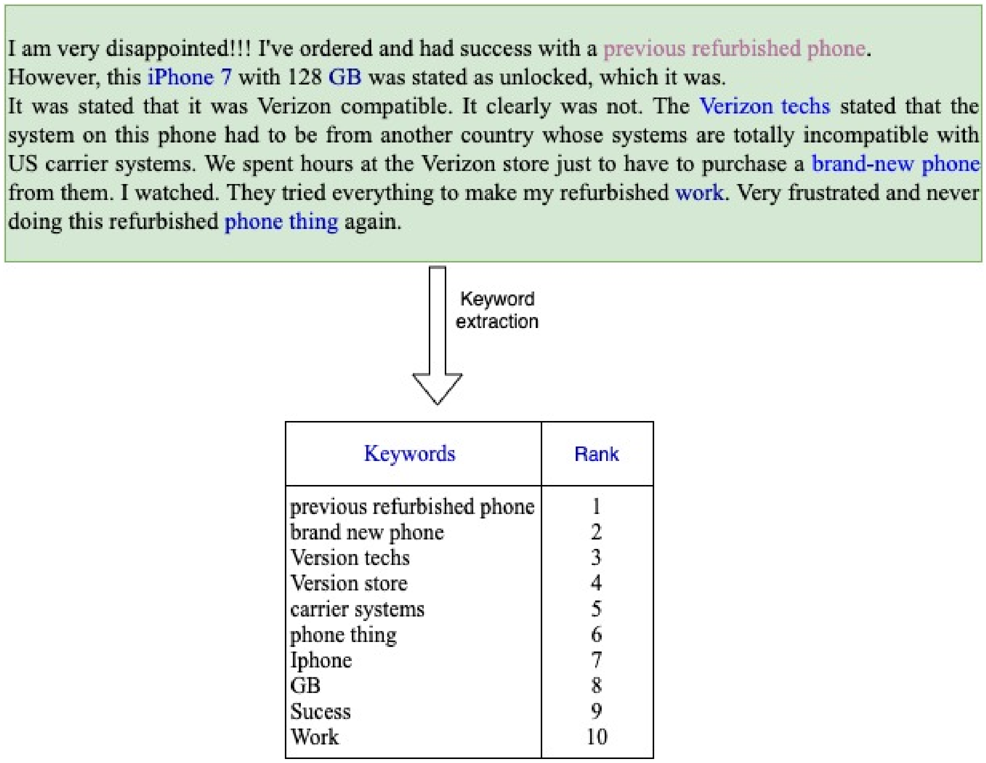


Figure 4.5: The illustration of keyword extraction

Static Aspect

The statistic features (SF) are defined by the producer and it shows the product's common attributes. For example, , the SF of mobile phone could be: "screen", "sharp", "color", etc. The static features are used conjunctively with the extracted features for ensuring that all aspects of the given product are considered. We merge the extracted features with static features for obtaining a set of features for a given product.

The merging of dynamic features and statistic features are used as users requirements for designers.

Aspect Extraction with AlchemAPI

The AlchemAPI is exploited as one of the component for the proposed system. The ultimate goal is to obtain key phrases from the review texts. We rank key phrases with respect to their priority in the review set. We will chose the top key phrases as aspect in product design. Those aspects of the given product will be re-evaluated by designers in the later phase.

For example, give the input text, we can perform keyword extraction to obtain a set of keywords with ranking score as shown in Figure 4.5

We also use AlchemAPI [2] for obtaining a set of keywords from the review text. Figure

[2]https://www.ibm.com/watson/alchemy-api.html

4.7 depicts the keywords extracted from the top customer reviews. Figure 4.6 shows the keywords extracted from the top critical customer reviews. The motivation is to see how the proposed framework are able to obtain key concepts. We also want to know what is the main differences between them. In addition, the contribution of the top critical and positive reviews to product design is also investigated.

top extracted keywords from top positive review

Keywords	Rank
32G memory card	1
Obviously tattered box	2
brand new item	3

top extracted keywords from top negative reviews

Keywords	Rank
line auto model	1
price range	2
large glass	3
f stop	4
camera	5
night time	6
Daylight	7
Photo	8

Figure 4.6: The top keywords extracted from top positive and negative reviews for Sony Camera

Figure 4.6 describes extracted keywords obtained by our system when performing it on the top positive and top critical reviews. Figure 4.6 also indicate the keywords and its relevance ranking to the review. It is easy to see that the number of keywords extracted from top critical reviews is higher than that of keyword extracted from top positive reviews. The proposed system is also verified when we collect customer reviews for the Laptop computer on the amazon website. Figure 4.7 depicts the top 10 keywords of extracted the top positive and top negative. The results demonstrate the same finding as reviews for the camera.

top extracted keywords from top positive review

Keywords	Rank
photo work	1
Heavy lifting	2
USB driver	3
Splash screen	4
Extra Storage	5
USB ports	6
HDMI ports	7
Clicker bottom	8
Internal Driver	9

top extracted keywords from top negative reviews

Keywords	Rank
Nice HD screen	1
SD card storage	2
Slow processor	3
Web surfring	4
Disk Driver	5
Track Pad	6
Low storage	7
Executable program	8
Storage card	9
Mouse	10

Figure 4.7: The top keywords extracted from top positive and negative reviews for Laptop computer

Supervised method: Aspect Extraction with Sequence Learning

In addition to the unsupervised method mentioned above, we study a supervised sequence learning technique for aspect extraction. Assume that we are given a sentence S consisting of sequence of words $W_1W_2...W_n$, we would like to find a sequence of aspects for the sentences. This task can be formulated as a chunking problem that finding a sequence of labels corresponding with a sentence.
For example: "I am pleased with the fast log on, speedy WiFi connection and the long battery life ($> 6hrs$)", the sequence of aspects would be "log on", "WiFi connection", "battery life".

Figure 4.10 shows an example of formulating the problem of keyword extraction as a sequence learning using the BIO tagging. Each word is assigned a label among three labels "B-AP": beginning of an aspect; "I-AP": inside an aspect, and "O": outside an aspect.

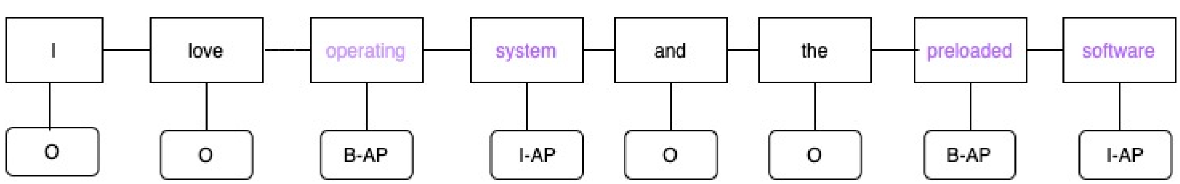


Figure 4.8: An Example of keyword extraction using sequence learning

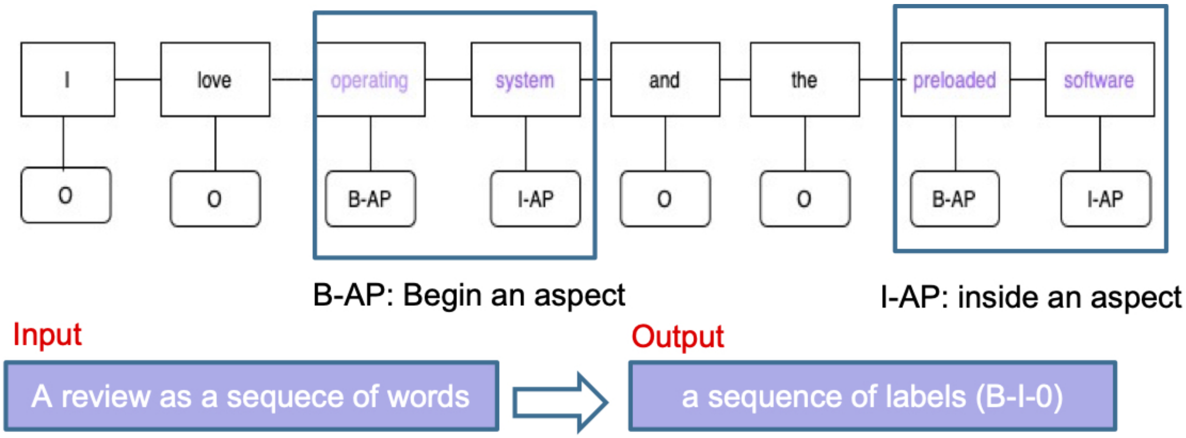


Figure 4.9: An Example of keyword extraction using sequence learning

Fortunately, we can exploit the state of the art sequence learning models for finding a sequence of aspects [58][56].

Along with the sequence learning model used in related works [58][56], we investigate the state of the art models which have obtained very good results in natural language processing tasks including BERT for sequence learning [3] and GCDT models[87].

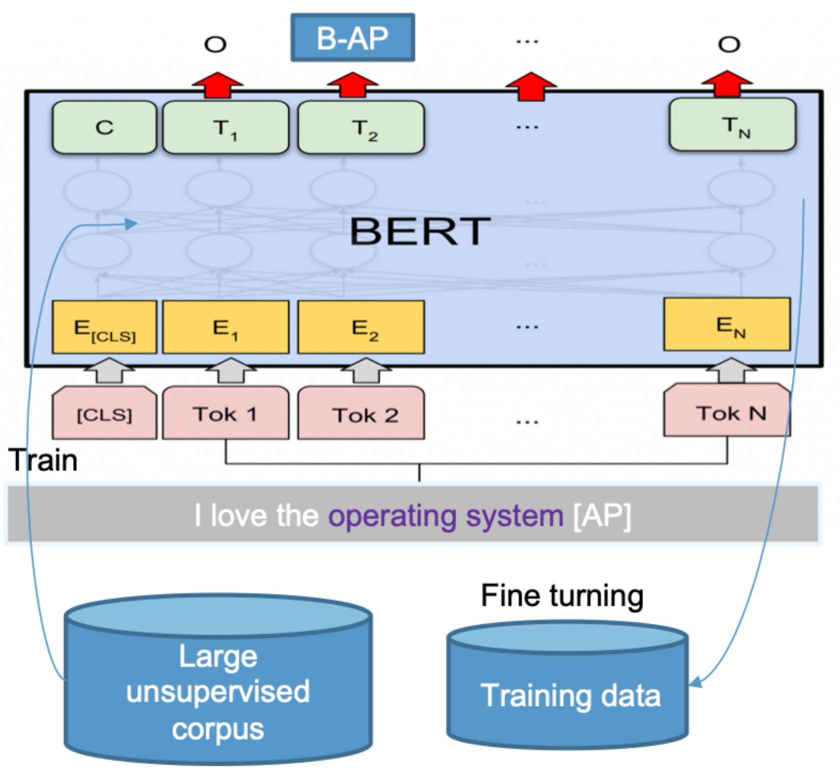


Figure 4.10: The Aspect Extraction using BERT model. B-AP means beginning an aspect, O mean outside an aspect

[3]https://huggingface.co/transformers/model$_doc/bert.html$

This is the first time GCDT and BERT models are used in the aspect extraction task, so, we would like to compare these models with other sequence learning models. Due to the limitation of computational time, we can only apply BERT-base for our task. If TPU computing is available, the BERT-large can be applied with an expectation that the performance of our aspect recognition would highly improve. The advantages of the method using sequence learning for Aspect Extraction are that it could help us to obtain a high performance for extracting aspects. However, the limitation is that we need to prepare the training data for the sequence learning models.

4.2.2 Multiple Review Summarization

The proposed multiple review summarization model consists of two major components. The first component finds all relevant sentences corresponding with an aspect. This process applies a information retrieval technique. The second component performs a summarization technique to obtain a summary of relevant documents.

Extracting relevant sentences with keywords

This subsection will show how to extract all relevant sentences with respect to a given feature. In order to do that the Lucena - a popular tool for information retrieval [4] is chosen for finding a set of relevant sentences corresponding to a particular aspect feature. Lucene will find all sentences that are similar to each feature. The co-sin similarity method is used for measuring the similarity score between a sentence and a keyword. The following equation shown how to calculate the similarity score between sentence A and sentence B.

$$\mathrm{Sim(A,B)} = \cos(\theta) = \frac{A.B}{||A||||B||} \tag{4.2}$$

We also utilize BERT [19] for encoding a sentence to a vector representation. BERT typically used a multi-layer bidirectional transformer encoder and apply two unsupervised methods including masked language modeling and next sentence prediction, to pre-train the encoder. The language modeling tasks aim at predicting masked tokens by utilizing the rich context between left and right. Sentence prediction aims at modeling the relationship between two sentences A and B. It is equivalent to binary prediction task to verify whether or not the second sentence B is the next sentence of A. We can make a fine-turn for BERT only adding additional output layer to obtain the state of the art models for a many tasks. The BERT is used for encoding sentences for our opinion summarization task. To know the idea of using BERT for similarity measurement, we consider some examples in Table 4.2. This example showed that BERT model can help us to obtain very accurate similarity score.

[4] http://lucene.apache.org/core/

Table 4.2: Example on the similarity measure with BERT transformer method

Sentence(A)	Sentence (B)	Similarity Score
A man is eating pasta	A monkey is playing drum	0.1945
A man is eating a pasta	A man is eating a food	0.840
The battery life is excellent	The battery life is great	0.8048
The battery life is excellent	great battery life	0.7244
The battery life is excellent	Screen is awesome, battery life is good	0.8126

Multiple document summarization methods

After performing the search component to obtain all relevant sentences with a given topic, we will conduct a summarization component to obtain important sentences regarding the feature. The popular Maximal Marginal Relevance (MMR) can be applied to reduce the redundancy in the sentence extraction process [9]. The key point of this method is to maximize the marginal relevance in the formula as follows:

$$\mathrm{MMR}(s_i) = Sim(s_i, C) - \max_{s_j \in S} Sim(s_i, s_j) \tag{4.3}$$

where s_i,C, and S are the candidate sentence, the set of relevant sentences to a particular topic, and the set of sentences already included in the summary, respectively. The cosine similarity measure between sentence vectors is used for computing Sim. We also conduct multiple-document summarization models [90] which used the MMR approach in selecting important sentences (except integer linear programming(ILP) and the baseline lead method) which can be summarized as follows.

Lead: The strong baseline method takes the top sentences being as a the summary for the document.

Centroid-based summarization: This method [69] aims at building a centroid based on the pseudo-sentence of the document. We select each word in the centroid C using the TF-IDF score. The score of each sentence is estimated by summing the three scores as follows: cosine similarity of the sentence with C, position weight, and cosine similarity with the first sentence.

TextRank[68]: This method builds a graph by considering each sentence as vertices and the edge is a relation between two sentences (overlap). We used the graph-based ranking method to obtain the score for each sentence. Note that each sentence is associated with its score. A greedy algorithm can be used for obtaining summary sentences.

LexPageRank: [21] It is similar to the text rank, we need to build a graph representation (G) of the documents. They key issue is to compute the importance score of each sentence. We applied the method of eigenvector centrality in the graph G and calculate the adjacency matrix of G by intra-sentence con-sine similarity. After that we can select the sentences as a summary of documents.

The ClusterCMRW [82]: This method stands for a cluster-based condition markov random walk model. It is based on a relax condition that we have a few topic themes in

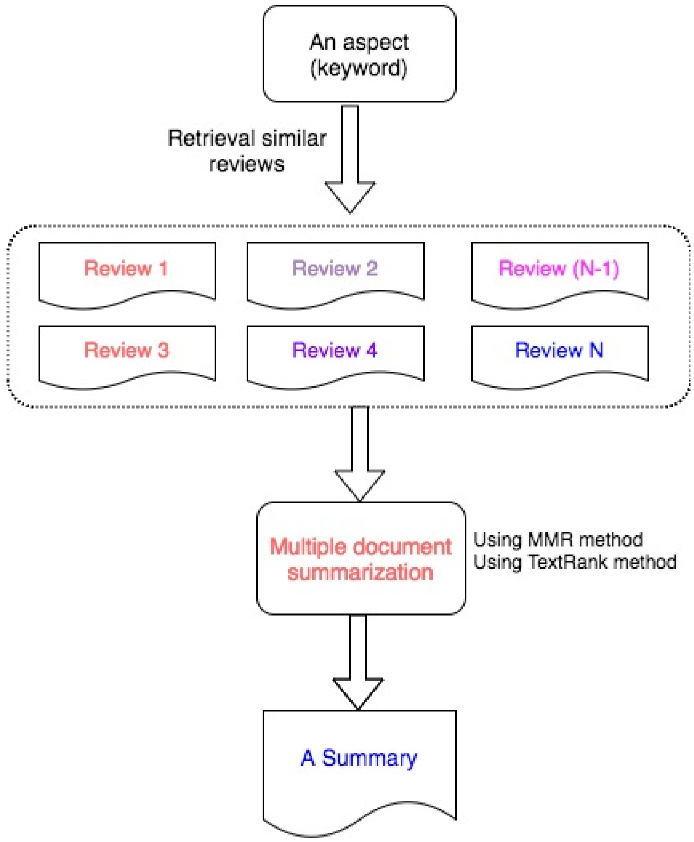


Figure 4.11: The Opinion summarization model

the documents. The sentences in an important theme cluster would be more salient than those in an another cluster. This method takes the link relationships between sentences and uses the cluster-level information. Selecting parameters in this model is not easy task so in our work we choose the default model[90].

ILP: Integer linear programming (ILP) method[23] considers the summary process as a combinatorial optimization problem. The algorithm will extract all bi-grams and their weighs in the documents (i.e using tf-idf). The summary is selected by finding a subset of sentences subject to the condition that the sum of bi-gram weights is maximize.

Submodular[49] and [52]: The summarization process is conducted by maximizing submodular functions subject to a budget constraint. The implementation of this method is based on [90].

Figure4.11 indicates the proposed multiple-document summarization model consisting of the two major procedures. The first procedure applies the search engine method to find a set of relevant reviews corresponding with the keyword. The second procedure uses text summarization techniques to obtain the summary.

Sentiment Classification

After obtaining a set of reviews corresponding with aspects, we then summary all relevant reviews to obtain a summary corresponding with the feature (for example, all sentences relating to screen). Then, we perform a sentiment classification model to classify review sentences into positive and negative. The sentiment classification is built by collecting the training data from the Amazon website (similar to [39] and used it along with the sentiment treebank of Stanford University ([67]).

In order to find a suitable sentiment classification mode, we investigate many machine learning models and deep learning models as follows: Support Vector Machine, XGBoost, Convolutional Neural Network [88], RNN-Capsule, BERT text classification, and Fasttext. Other machine learning models have been introduced in the helpful review identification parts. In this subsection, we focus on introducing RNN-Capsule [81], which is an extension of CNN.

The Recurrent Neural Network-Capsule (RNN-Capsule) is defined as a capsule model based on Recurrent Neural Network (RNN), and it is adapted for the sentiment classification task. One capsule is constructed for each sentiment category. It can either be positive or negative. Each capsule consists of the following components: an attribute, a state, and three modules, including (representation module, probability module, and reconstruction module). The attribute of a capsule is the assigned sentiment category. RNN-Capsule model showed that it could attain the state of the art results in sentiment classification. Therefore, we would like to compare its performance with other machine learning models. Figure 4.12 depicts the RNN-capsule framework for sentiment classification.

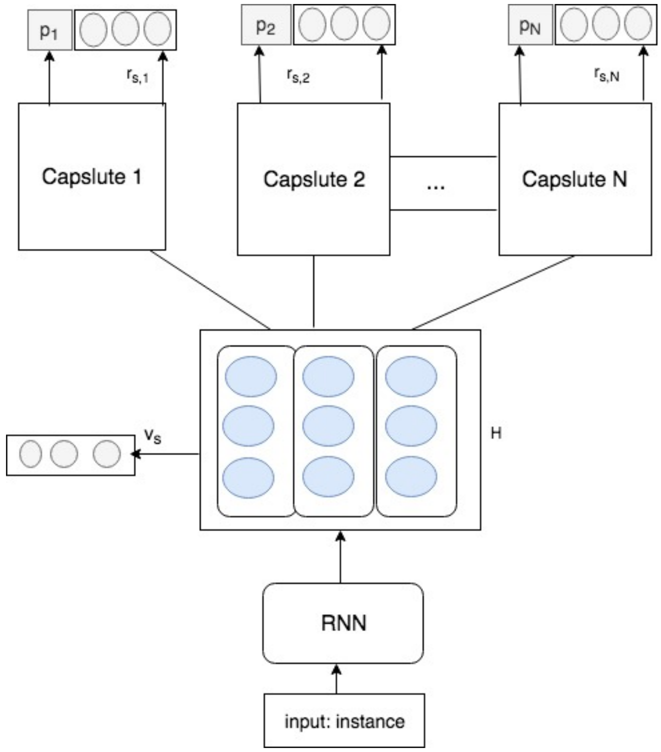


Figure 4.12: The RNN-capsule for sentiment classification [81].

Besides, similar to the helpful identification model, we used the FastText method to classify a review into positive (+) and negative (-) categories. The reason why we choose FastText [38] is that this model can deal well with noise text, which often occurs in online reviews. Besides that, we also investigate other conventional machine learning models, including Support Vector Machine, XGboosting, RNN-Capsulate, and BERT for sentiment classification.

Table 4.3 shows the contribution of sentiment classification for the aspect feature "battery life". It indicated the results when we perform a sentiment classification model. Note that the notation ("+") and the notation ("-") mean positive and negative, respectively.

Table 4.3: Example on sentiment classification with respect to concept **battery life**

Label	Review
positive ◡̈	The battery life for this phone is really good as well .
positive ◡̈	The battery life on this phone is very substantial.
negative	Poor battery life and occasionally slow OS
negative	Short battery life, takes a while to connect to GPS
negative	Battery life is rubbish
negative	Chunky, terrible battery life
negative	Battery could be improved

4.3 Experimental Results

To verify the performance of the proposed framework, we will evaluate the accuracy of each component including sentiment classification and aspect extraction. We begin with our evaluation on sentiment classification in the benchmark data. After that, we will evaluate the performance of the aspect extraction and summarization components.

4.3.1 Sentiment Classification

The training data for our learning model are collected from the Amazon website are used with the sentiment tree bank of Stanford University [67][59]. We investigate many machine learning models and deep learning models to find suitable one for our framework. We choose the FastText tool for learning sentiment classification model because its training is very fast. The training data and testing data are obtained from the Kaggle competition [5]. The experimental data consists of 3600000 samples and 400000 samples for training data and testing data, respectively. We compared Fasttext with other sentiment classification models using capsules network [81].

On the other hand, the state of the art techniques used pre-training model on very huge training data and make a fine-turning for other data to obtain very accurate performance. BERT transformer model is the tool for pre-train [19]. We run this tool using the BERT-base model and compare with other machine learning models. It is similar to the chapter 3, we also investigated SVM and XGBoost models for sentiment classification. The reason we choose SVM and XGBoost is that they are two strong conventional machine learning models.

Table 4.6 shows the comparison among BERT classification, RNN-Capsule, Fasttext, XGBoost, and SVM on the same test data. The results indicated that BERT attain the best accuracy and Fasttext is competitive with BERT.

Table 4.4: Experimental results for Sentiment Classification on the Amazon dataset

Methods	Accuracy
SVM (using linear kernel)	89.9
XGBoost (using bag of words)	87.5
Fasttext (not using ngram)	91.6
Fasttext (using ngram=2)	**92.6**
Fasttext (using ngram=3)	92.5
RNN-Capsule [81]	90.6
CNN	94.1
BERT classification	95.6

Since the BERT classification obtained the best performance in the dataset, so we selected BERT classification for using in our framework.

[5]https://www.kaggle.com/bittlingmayer/amazonreviews/home

It is noticed that in case we need to save computational time for sentiment classification, we can choose the Fasttext (with ngram=2). One of the advantages of Fasttext is that the computational time of its training and testing is fast and does not require colossal memory and GPU computation.

We then used the model to learn from the Amazon dataset to perform sentiment classification to check whether or not a sentence is positive or negative.

4.3.2 Aspect Extraction

To verify the Aspect Extraction models, we tested the proposed system on the benchmark data set. For this reason, we selected the SemEval2014 dataset [64] for our evaluation because it is often used in verifying the accuracy of aspect extraction in the computational linguistic community. Table 4.5 shows the statistic of training and testing data as well as their numbers of aspects.

Table 4.5: Aspect Extraction on SemEval2014 for laptop data

Number of train sentences	3045
Number of train aspects	2358
Number of test sentences	800
Number of test aspects	654

We conduct the experiments using the same evaluation method described in [58]. That means an Aspect part is considered to be correct if and only if all its words are predicted correctly. *Precision*, *Recall* and F_1 scores are then calculated as follows:

$$precision = \frac{\#\text{correct parts}}{\#\text{predicted parts}}, recall = \frac{\#\text{correct parts}}{\#\text{actual parts}} \tag{4.4}$$

$$F_1 = \frac{2 * precision * recall}{precision + recall} \tag{4.5}$$

We consider the following models to compare with the BERT methods.

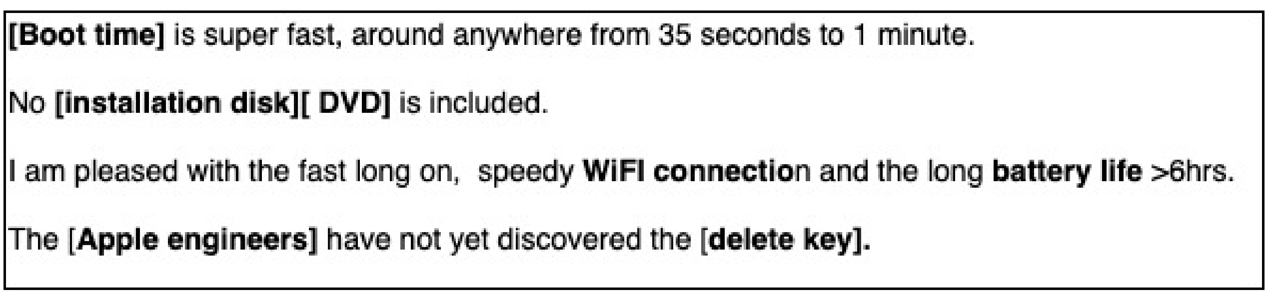
- BiLSTM and BiLSTM-CRF is the bidirectional long short term memory and its extension with the final layer CRF, respectively - it mainly applied for sequence learning.
- SeqSeqAST and DOER models are advanced sequence learing models taking from previous work[56] [58]
- GCDT is a global context enhanced deep transition model for sequence learning. It applies the first time for aspect extraction

Experimental results showed that our BERT model outperformed other sequence learning model in terms of F1 score for aspect extraction. The GCDT [6] and DOER models attained promising results that are competitive with the BERT sequence model. The BERT model obtained significantly higher than the baselines BiLSTM and BiLSTM-CRF models.

Table 4.6: Aspect Extraction on SemEval2014 for laptop data

Methods	F1 Score
BiLSTM	75.6
BiLSTM-CRF	77.2
SeqSeqAST [58]	80.3
DOER [56]	82.61
GCDT	82.26
BERT Sequence (BERT-base)	**83.8**

Since the BERT sequence model obtained the highest result, so we will consider to use it in our framework when we test with Laptop and Electronic data. Figure4.13 demonstrate the output of performing aspect extraction with BERT model. The BERT sequence model predicts correctly for the first sentence to the third sentence. In the last sentence, it generates two aspects, including [Apple engineers] and [delete key]. However, the actual output is only [delete key] is correct.


[Boot time] is super fast, around anywhere from 35 seconds to 1 minute.

No **[installation disk][DVD]** is included.

I am pleased with the fast long on, speedy **WiFI connection** and the long **battery life** >6hrs.

The [**Apple engineers]** have not yet discovered the **[delete key].**

Figure 4.13: An example of user requirement on the aspect

4.3.3 Multiple document summarization

To evaluate the performance of keyword extraction and summarizing, we will conduct our experiments with the keywords extraction combining with various multiple document summarization methods.

The publicity released BERT model is used with our system [7] to initialize the sentence encoder. Regarding the text summarization methods, we consider the following text

[6] https://github.com/Adaxry/GCDT
[7] https://github.com/google-research/bert

summarization models to select appropriate one.

- The Lead baseline model
- The Center based model[69]
- The TextRank model [68]
- The LexPageRank model
- The Submodular model [49] and [52]
- the cluster based model [82]
- The Integer Linear Programming- ILP method [23]

Figure 4.14 indicates the output of performing the proposed framework on the collection of reviews. It clearly shows the results of the query: "battery life"

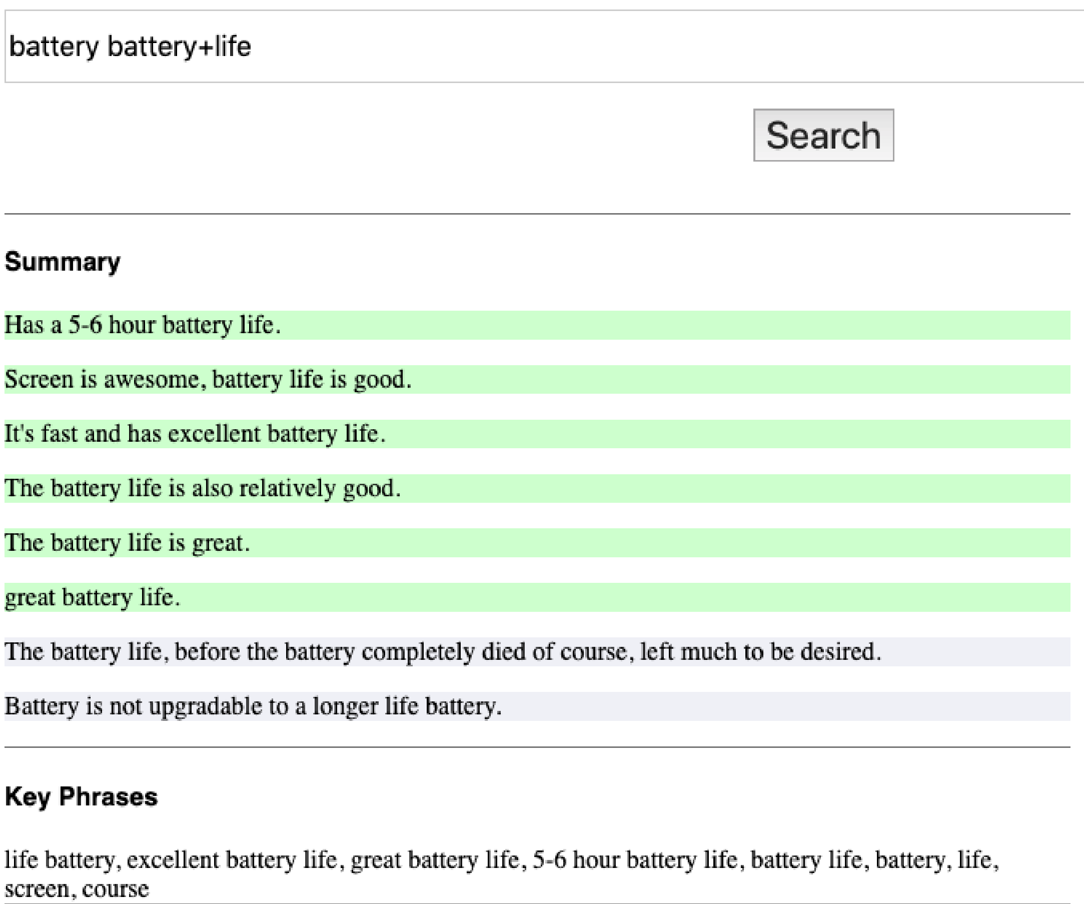


Figure 4.14: An example of user requirement on the aspect

Evaluation methods The summaries are used as gold-standard references for evaluation using the ROUGE-scores ([51]).

$$ROUGE - N = \frac{\sum_{s \in S_{ref}} \sum_{gram_n \in s} Count_{match}(gram_n)}{\sum_{s \in S_{ref}} \sum_{gram_n \in s} Count(gram_n)} \tag{4.6}$$

where n, $Count(gram_n)$ is the length of n-gram and the number of the n-gram in the reference, respectively. $Count_{match}(gram_n)$ is calculated as the maximum number of n-grams co-occurring in s and the S_{ref}. The F-score of ROUGE-1, ROUGE-2, and ROUGE-SU are used as the evaluation metrics.

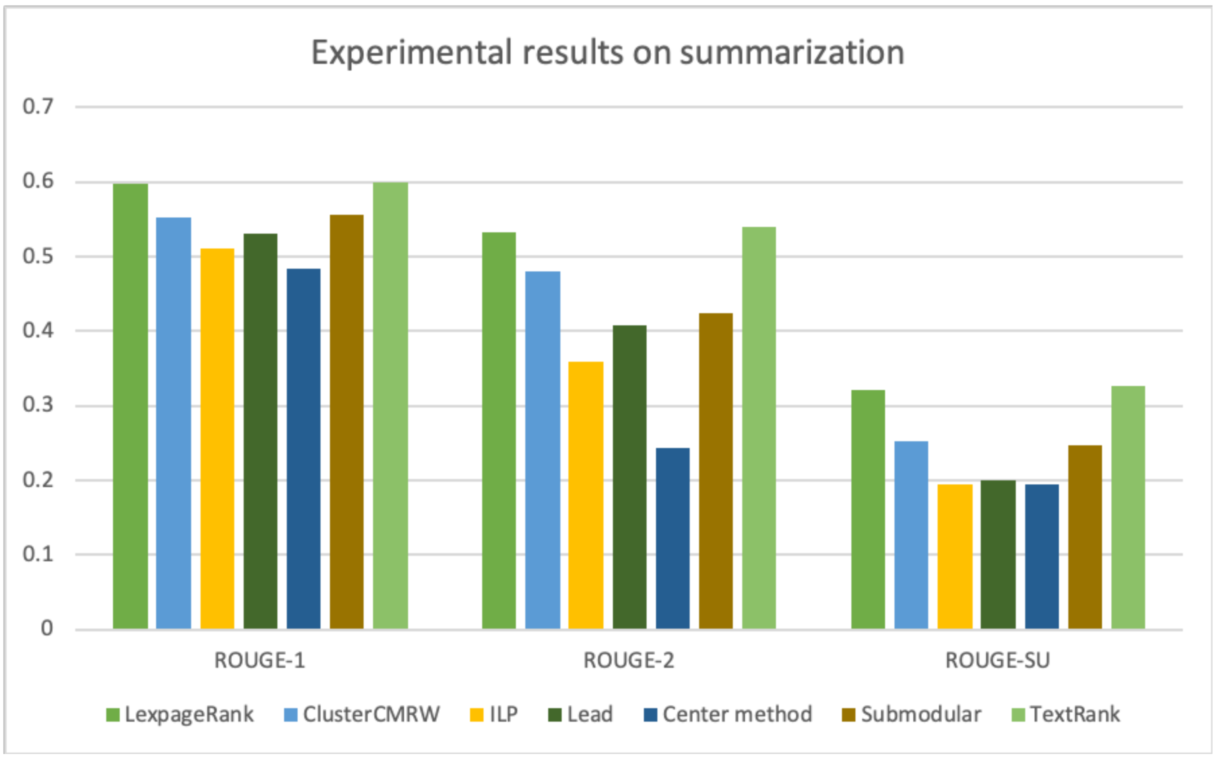


Figure 4.15: The comparison of text summarization methods on opinion reviews

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Figure 4.3.3 shows our evaluation when testing different MDS methods in summarizing review documents about the mobile phone. We perform those MDS mentioned above on ten opinion reviews and conduct a compare our results with the standard summary annotated by human. We evaluate those MDS using ROUGE scores [51]. Figure 4.3.3 showed that the proposed system obtain a very good result for being used with designers. The ILP and LexpageRank method show promising results and the lead-based method is strong baseline. The results showed that TextRank method outperformed other methods in ROUGE-1 and ROUGE-2 scores, so we choose TextRank for being used in the proposed system. Another multiple document summarization methods attain a less accuracy than ILP and TextRank methods because we actually used the default parameters. We need to find a mechanism for turning parameters to obtain more better performance and we open it in the future work.

In the next section, we will conduct our case studies when working with designers.

4.3.4 Human Evaluation

We invited 50 designers to evaluate the proposed system. Each designer will be asked to judge the proposed system in terms of their responsiveness score for using the proposed system for extracting user requirements. Human assessors were required to give a score (from 1-5) for each summary based on its content and coverage of important topics in the review set. Score 1 is the least responsive and five being the most responsive. We consider three options: Summarizing opinion, Aspect Extraction (Keyphrase), and Sentiment and helpful review classification. We tested with the aspects "color" and "screen" on Fashion and Electronic data, respectively. The score of the proposed system in three components: Opinion Summarizing, Aspect Extraction, and Sentiment classification showed promising results. The results suggested that our system is satisfied with designers in using it for extracting user requirements from online customer reviews. Therefore, we can use the proposed system for supporting designers in terms of designing products. In future, we would like to investigate more experiments with other aspects and products than the aspects mentioned above.

Table 4.7: Designer Evaluation on Electronic and Fashion Data

Data	**Electronic**	**Fashion**
Opinion Summarization	4.3	4.1
Aspect Extraction	4.1	4.0
Sentiment Classification	3.9	4.0
Helpful review identification	3.9	4.0

4.4 The Cases Study II

In this section, our case study with Nokia phone will be discussed for verifying the performance of our framework. We begin with our process of collecting opinion documents. We collect both normal reviews and top reviews for our case study. After that, the proposed framework will be used for obtaining URs. Thereafter, the URs are sent to designers by means of a questionnaire which is shown in Figure 7.1.

Nokia mobile phone Case Study

We collect reviews about the Nokia mobile phone and perform the proposed framework to extract user requirements (URs). The two top review documents are obtained among 90 review documents. Following this, we conduct aspect feature extraction and opinion summarization components to capture user requirements(URs). These URs are provided for designers in the process of designing new aspects for the product. There are two types of URs are considered for designing mobile phone as follows. The first type relates to the hardware. The second type considers the shape, the "color, and the "structure" of the mobile phone. For validating the URs output in product design, we conducted the questionnaire for checking the usefulness of the proposed framework for designers. We used the answers from the questionnaire to evaluate how URs can represent the opinion of the actual products. The questionnaire is intended to be used by designers for further improvement and development of the product. We provide a list of aspects that are ranked by the importance score of the proposed system. In addition, the URs include a list of positive and negative of the highest-rated requirements from the opinions of users. Note that since URs are obtained by performing automatically, so some URs are not precisely defined. Finally, we list questions regarding every test case. Figure 7.1 shows how the questionnaires are used for evaluating the outputs of the proposed framework.

We provide the outputs to the designers as follows.

- The positive and negative (advantages and disadvantages) feature aspects
- The outputs of users requirements extraction.
- The aspect features of the product.

All designers are given a half-hour for reading the outputs to fill the answers in the questionnaire. The main goal of our work is to verify how the proposed framework can contribute to improving the Nokia phone, so to achieve that, the designers were provided a list of URs, which include a list of features and the corresponding customer reviews.

The features are expected to have an influence in terms of designing products. For example, the mobile phone's color may affect perceived luxuriousness, and the arrangement of a display and its relevant buttons may affect perceived harmoniousness.

Table 4.9 shows the results obtained from the evaluation of the designers. Table 4.9 showed that there are 41 URs (32%) per 125 total extracted URs, were selected by all designers. This results demonstrated that the extracted URs is helpful for designers.

4.4.1 Questionnaire Results

Table 4.9 depicts that all designers are marked Yes for all questions (except question 2). We conduct an interview with designers by asking several questions regarding to user requirements within in the questionnaires.

The questionnaires indicated that our framework is useful in terms of "shape", "function", and "content". Table 4.9 lists our finding as follow:

- The results clearly demonstrated that the URs regarding "shape, function, and contents" are useful and save time for designers.
- The system's outputs enrich design knowledge. It is useful for designers in designing the product.

Table 4.8: Evaluation of the proposed method for product design in the Nokia case

Requirement List	Score	votes	Requirement List	score	votes
memory	100	3	remove battery	29	3
Weigh	100	3	main menu	36	3
Display	100	3	quality picture	41	3
Shape	100	1	internal memory	55	1
Color	100	3	TFT color display	38	1
Screen	100	3	pixel camera	36	3
Size	100	1	Picture quality	55	3
Wide range	29	1	TFT color display	38	1
white balance	29	3	Battery life	62	3
video calling	46	3	Second VGA	29	3
text messages	46	3	Mini SD	29	3
Symbian operating system	42	1	Drain Battery	29	1
switch off	36	3	Music Player	36	3
stereo speakers	41	3	USB cable	36	3
standby time	29	3	VGA Camera	29	3
sound quality	55	1	Visual Radio	29	1
software update	29	1	Data cable	46	1

Table 4.9: Questionnaire results (N-Phone: Nokia Phone)

Questions	***Designer 1***	***Designer 2***	***Designer 3***
	Nokia-Phone	Nokia-Phone	Nokia-Phone
Question1: Function of Product	Yes	Yes	Yes
Question2: Shape of Product	Yes	Yes	Yes
Question3: Content of Product	Yes	Yes	Yes
Question4: Information Usefulness	Yes	Yes	Yes
Question5: Time saving method	Yes	Yes	Yes
Question6: Enrich knowledge	Yes	Yes	Yes
Question7: Help of advantage-disadvantage	function	function/memory	function
Question8: Significant component	Yes	Yes	Yes
Question9: Evaluate for futher design	useful	useful	very useful

- It showed that the presented URs with respect to "product functions", "product shapes", and "product contents" (software) are informative for designers.
- It showed that designers could save time in collecting URs. The features list is helpful for designers and support designers.
- The shape components significantly contribute to the improvement and development

of the product.

- The Positive (Advantage) - Negative (Disadvantage) list of features supports designers in product design.

- The URs information presented is evaluated as very useful for future design

The designers got a consensus that the outputs are enriching design knowledge and helpful in designing the product. It demonstrates the success of bridging between URs and designing of products.

4.5 More case studies for electronic and fashion products

In this case study, we mainly focus on some significant features of electronic and fashion products. We choose these products as additional case studies because we plan to utilize the results for the next chapter when combining it along with cultural aspects. We collect online documents from amazon websites which is stored in the address [8], we take the customer reviews on electronic data and fashion data, and storing them into the proposed system. In addition, we add the number of reviews on laptop which is used in SemEval 2014 competition[9]. We crawler the amazon website to take all the data about Uniqlo (totally we had 9,037 documents). We then perform our system to obtain user requirements. Two types of products are considered in our model, which includes the electronic product (phone, laptop, camera, vacuum, and smart speaker) and fashion product (skirt, bag, phone cover, hat, and other). We conduct an interview process by using a questionnaire form. We asked the participant by 50 designers which come from Vietnam, Japan, and China. The google form and the word file are used for the interview. (In china, they could not use google form, so we need to send the questionnaire via the word file). Note that the condition for selecting designers is that the designer should have background on product design and/or fashion design. Otherwise, they should have experience in designing products or they are senior designer. The information about designers are sketched in Appendix.

Each designer will be asked to answer the questions in the questionnaire. Along with the questionnaire, they are provided the user requirements, and they were asked to choose which user requirements can contribute to designing products. The proposed framework is made available in the following the specific address [10]. To focus more on the interaction with designers, we consider the significant features which are mainly used for electronic products. The procedure can be used as follow. For each major aspect, a designer can typically search the aspect and obtain all relevant user requirements. For example, they can search all customer reviews concerning about the aspect "screen", the framework will

[8]http://jmcauley.ucsd.edu/data/amazon/

[9]http://alt.qcri.org/semeval2014/task4/

[10]The address of the system is made available via http://150.65.242.86:8080/

show the list of reviews and classifying them into positive and negative categories. We also provide a component for users that they can take user requirements by pasting the link (i.e [11]) about customer reviews on the amazon website to the system.

Figure 4.16 depicts the ratio of how many designers could vote for choosing the features in designing electronic products.

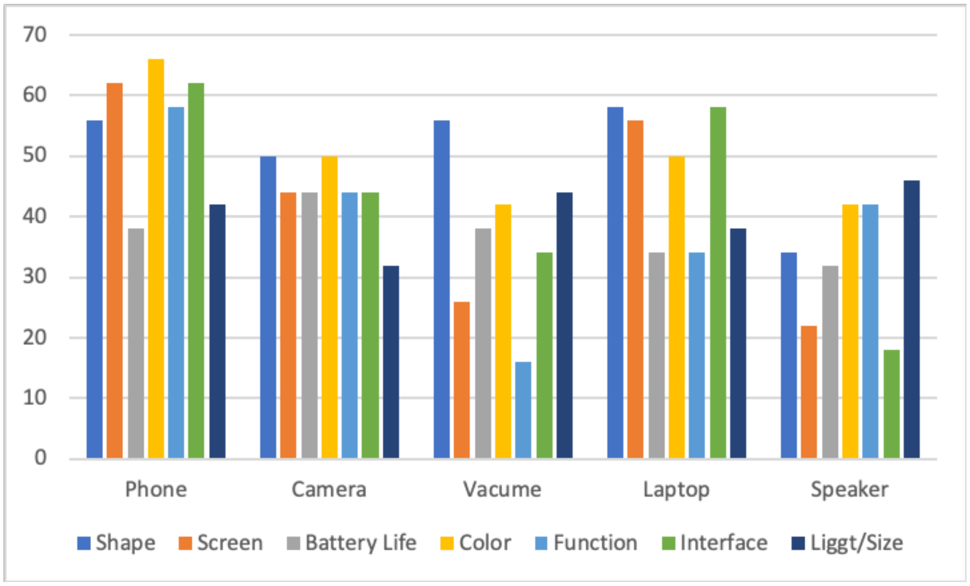

Figure 4.16: Designers choose for UR on the aspects with electronic products

The results showed that the "shape" features voted with the highest result among designers for the Laptop. The "function" and "interface" features are important for designing mobile phones. Regarding the "battery life" features, the designers agree that they are important for all electronic products, including Phone, Camera, Vacuum, Laptop, and Speaker. It is supervised that many votes for receiving for Camera. The "screen" feature is favorites for Phone and Laptop. This can be understood because they are important features for being used with a mobile phone and Laptop.

Figure 4.16 depicts the ratio of how many designers vote for choosing the features in designing fashion products. The results indicated that the "shape", "color", and texture equally contribute to designing a bag. The "light" feature is more priority than the "size" feature. It is similar to the "skirt", "hat", "PhoneCover", and "clothers". The "texture" feature is selected by many designers.

Analyzing the preference of designers voted in the electronic and fashion products, we found that the outputs of user requirements extraction would help designers to find some interesting points for designing a product. It is also enabled them to access vast and useful information in designing products.

[11]https://www.amazon.com/product-reviews/B07NP1676G/ref=cm$_c r_a rp_{dv} iewpnt_l ft?ie = UTF8 filterByStar = positivereviewerType = all_r eviewspageNumber = 1reviews - filter - bar$

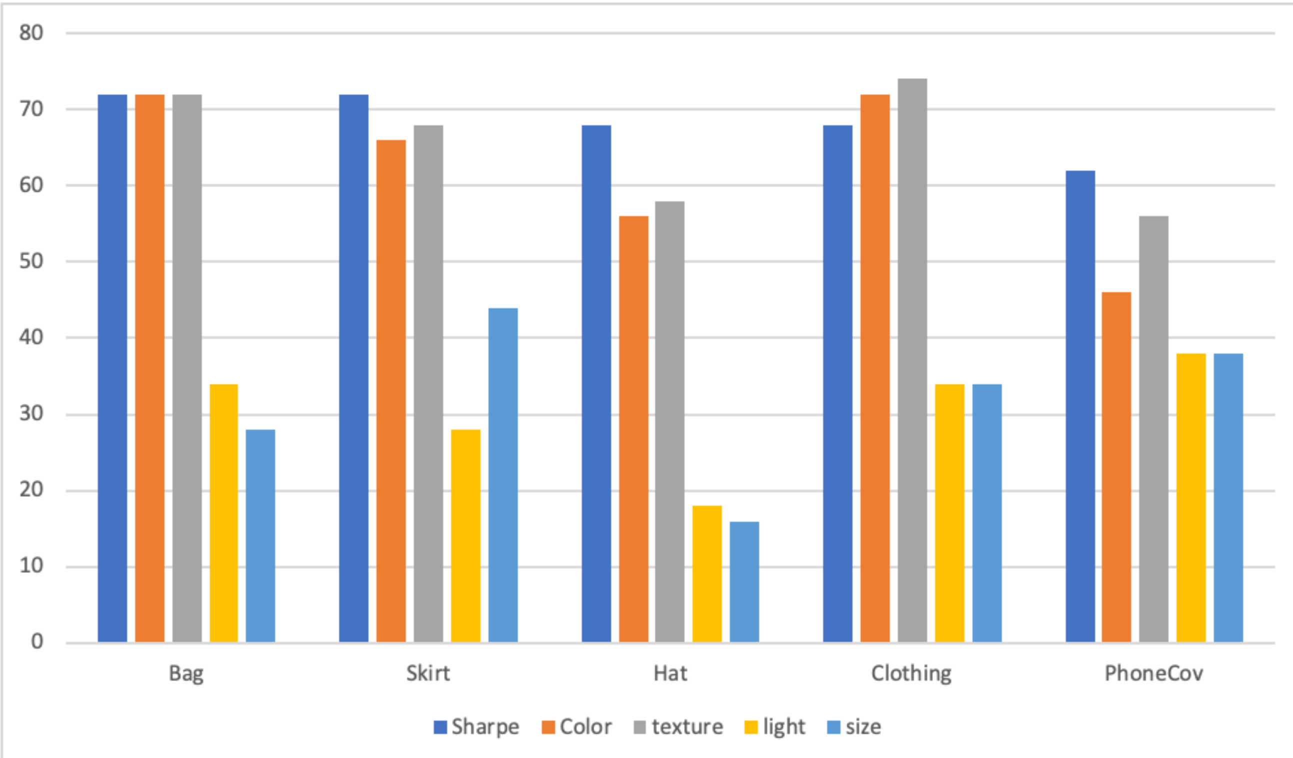

Figure 4.17: Designers choose for UR on the aspects with Fashion Products

4.6 Summary

In this chapter, we have proposed a new framework for extracting user reviews from online shopping sites. Our work showed that the framework could support designers in the early phase of the design process. In addition, the proposed method can extract aspect features and extract all reviews relevant to aspect features and classify them into positive and negative. Experimental results on the standard data set showed that sentiment classification demonstrates a very promising result. The keyword extraction component showed an efficient way of extracting promising keywords which can provide potential concepts for designers. Experimental results of the text summarization showed that our model has a good performance in summarizing customer reviews. In the second case study, we provide a summarization approach with sentiment classification to classify opinions into positive and negative. As a result, the designers can effectively use the tool to extract key information from a large scale of data set. Furthermore, the results of the case studies promisingly demonstrated that the proposed system is useful for designers in designing both fashion and electronic products. In future work, we will consider collecting reviews on social networks such as Twitter and Facebook. Investigating an appropriate method for dealing with different languages and consider cultural aspects for product design.

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Chapter 5

Cultural Attributes for culture-oriented Product Designs

5.1 Introduction

According to our knowledge, the user requirements can be different from country to country due to the different of culture. Design studies have shown that cultural attributes can be seen as important factors for developing products from country to country. Culture, design, and their interaction make for an exciting research topic in this globalized world. Users are increasingly looking for differentiation in the products they own, as shown by Delaney et al. (2002)[17] and Aula et al. (2003)[62]. The research of using cultural oriented product design has been investigated in many works.

In this study, we investigate the contribution of a cultural attributes in product design and verify the possibility of integrating them with user requirements in designing culture-oriented product.

In addition, we discuss the relationship between culture and design, culture and the designer, and culture and the user. We also address different strategies for incorporating culture into design and the design process while designing for different cultures. For the sake of completeness, a brief overview of other research in the area of culture and design is laid out in this paper. Furthermore, we will show our investigation into cultural items for product development. We will present a framework for culture-oriented product design, which is the combination of user requirement extraction, along with the process of brainstorming using cultural factors. We also evaluate the contribution of user requirements and cultural attributes in product design by conducting an interview with designers from Vietnam, Japan, and China.

The chapter is organized as follows. The first section presents related work on cultural oriented product design which show fundamental background for culture in product design. The second section described the proposed framework for culture oriented product design. The final section will give conclusion and future work.

5.2 Culture-oriented product design

This section focuses on current methods and approaches used in design across different cultures. General approaches of globalization and localization/customization to provide to users from different cultures are reviewed first, followed by a review of some of the different approaches to design across cultures.

Culture-oriented product design

The culture-oriented product design model, or COD [60], is the result of a study discussing an experimental design approach in which participants were challenged for transforming and encoding sociocultural factors into features of product design. There are three interrelated phases in COD: categorization of sociocultural factors (user domain), integration (designer domain) and cherished, culturally orientated products (product domain). This model allows an assessment of how different elements of culture interconnect in the conceptualization of products with local relevance. This proposed model aids the design of products that consider user input as much as possible during the early stages of the design process. The work of cultural-oriented product described in [66] suggests a four-step process to achieve a balanced cultural fit for products as follows:

- (1) Research into a proper cultural configuration;
- (2) Integration of the findings into the design process;
- (3) Development of design concepts based on the model;
- (4) and contextual evaluation of design by listing potential users.

However, it is presumed here that the intended user's cultural preferences and expectations can be more appropriately understood if the designer is from the same culture as that of the user.

Cross-cultural user research

Another area of research related to culture and design is cross-cultural user research which focuses exclusively on the development of methods for conducting user research across different cultures. The work described by Lee et al.(2007) [47] showed how cultural differences can influence the process and outcome of user research; they performed a probe, a usability test, and a focus group interview in the Netherlands and Korea. Similarly, the authors in (2007)[13] discuss how usability tests are not the same worldwide. As a result, some researchers have suggested different ways of dealing with cultural differences during user research. For example, Chavan (2005)[10] introduces a number of culture-dependent methods for user research such as the Bollywood Technique and Emotion Ticket. Another approach [12] suggested templates for culture-specific usability testing. Similar research can also be found, suggesting different methods to overcome cultural barriers during user research. The work presented in [57] showed an interesting study on culture-oriented product design using both cultural items in cultural-pictorial inspiration (CPI) and cultural-textual inspiration (CTI). The authors pointed that the cultural features generation is an important stage in cultural product design activities. It suggested that we should attach great importance to extracting cultural features from cultural-textual inspiration (CTI) and fully excavate design features from cultural relics.

5.3 User requirements and Cultural Attributes for Product Design

As stated in the previous chapter, we can extract user requirements for product design. In this chapter we propose a framework using user requirements extraction along with cultural aspects for product design. The aim of our research is to illustrate that we can make a product more friendly with local users with regarding to user requirements which are sensitive with product design. In addition, we also want to show that for each country users are more friendly with traditional and local items, if one can design product which are reflected to these items then the designed product would be more friendly to the local users.

In the scope of our research, we conduct the following methods as follows.

1) We first perform our system to gather user requirements with respect to some feature aspects including: 2) We aim at tackling two kind of products: Electronic and Fashion products for our product design.

5.3.1 The proposed framework for culture oriented product design

In this subsection, we present the proposed framework which combines user requirements extraction and cultural aspects for product design. First, we will review the culture-oriented methodology for product design.

Figure 5.1 showed the proposed framework consisting of the following step which is based on the model described by [32][66]. It suggests four steps and ten design procedure for providing designers a systematic method in terms of designing a cultural product. The four steps and ten procedures of the cultural product design process are sketched as follows

- (Step I) identification (telling a situation),
  - (Procedure 1) Discussing the condition: Designers refer to discussions for understanding cultural products. They should have explicit understanding of design aspirations. A preliminary prioritized attributes hierarchy for product should be developed.
  - (Procedure 2) Recognizing the trend: This procedure will based on the cultural attributes for observing, comparing and incorporating relevant issues including

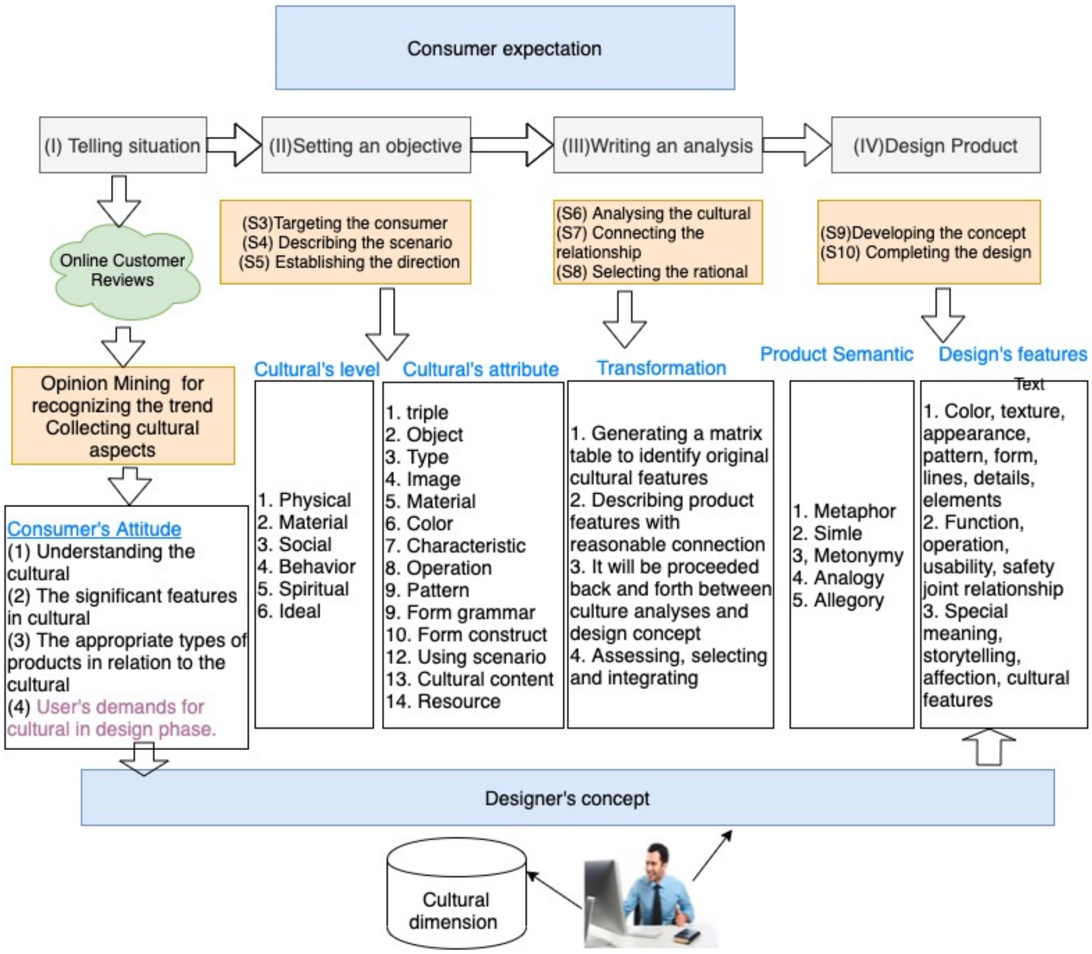


Figure 5.1: The proposed culture-oriented product design framework

economic developments, social trends, technological applications, and related existing products into the new product design.

- (Step II) investigation (setting an objective),
  - (Procedure 3) Targeting the consumer: This procedure aims at making a good observation of customer needs and exploring the consumer society for defining a product image with meaning and style derived from culture features concerns.
  - (Procedure 4) Describing the scenario: In this step, designers will be allowed for describing user's scenarios who have a preference for a particular style and identify with the features, meaning, category, and appropriateness of the product.
  - (Procedure 5) Establishing the direction: this procedure establishes a design specification, which aims at identifying the goal, function, target group, and limitation of the design. All of these concerns should match attitudes of consumers.

- (Step III) interaction (writing an analysis),
  - (Procedure 6) Analyzing the culture: This step will base on cultural layers for generating a matrix table in order to identify original cultural features including tribe, object, type, image, material, color, characteristic, operation, pattern, form grammar, form construct, formation, using scenario, cultural content, and resource.
  - (Procedure 7) Connecting the relationships: This procedure will base on reasonable connections such as product semantics, describe product features and develop a product with these cultural attributes. The analysis and synthesis will be processed back and forth between cultural analyses and design concepts.
  - (Procedure 8) Selecting the rational: assessing, selecting, and integrating semantically feasible manifestations into expressive wholes. In addition, describing the product performance and sketch the preliminary design image.
- (Step IV) an implementation (designing a product).
  - (Procedure 9) Developing the concept: this step is referred as the concept development and design realization by figurative product semantics (e.g. metaphor, simile, metonymy, analogy, and allegory), in order to transform the cultural meaning into a logically correct cultural product.
  - (procedure 10) Completing the design: examining the details and integrity of the cultural product as product features, supply cultural attributes to transform them reasonably into the product performance.

One of the key issues for exploring the cultural aspect of product design is how to recognize the trend of collecting cultural aspects. Unlike the original framework described in [32] [66], we would like to utilize the proposed user requirement extraction framework described in the previous chapters. We perform our tool to extract user requirements and opinion reviews from a large size of customer reviews. We can consider them as potential keywords for recognizing trends in product design. As indicated in Figure 5.1, user requirements extraction can be exploited in both Step I and Step II of the culture-oriented product design framework. In Step I, it will be applied for recognizing trends, and in Step II, it can be applied for targeting customers and understand the customer needs. In addition, with the explosion of social networks, one can conduct a design process by referring to many available designed items via observing social network. Pinterest is a popular social network for designers, and we consider to use it in the proposed framework. With the cultural keywords, Pinterest will be used to find more related items, and it will provide for the early phase of product design.

Figure 5.2 shows the list of similar images when you use Pinterest to search with the cultural keyword "Ruong Bac Thang".

After obtaining the list of similar images in Pinterest, the designers will start to do the brainstorming process. It means that their knowledge is enriched with more information.

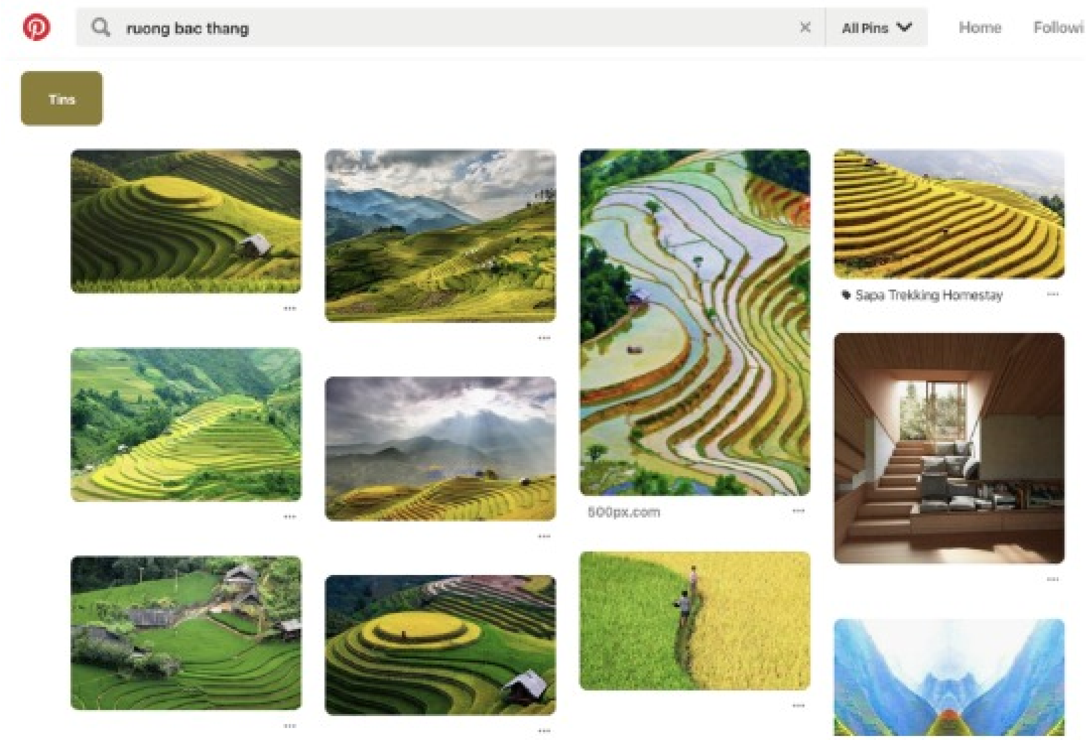


Figure 5.2: Vietnamese culture: the proposed framework

Figure 5.3: The outputs of using Pinterest for searching similar pictures and Concepts

Figure 5.3 shows the list of cultural items can be helpful for designers in terms of design creativity.

In summary, the proposed framework is sketched in the Figure 5.4

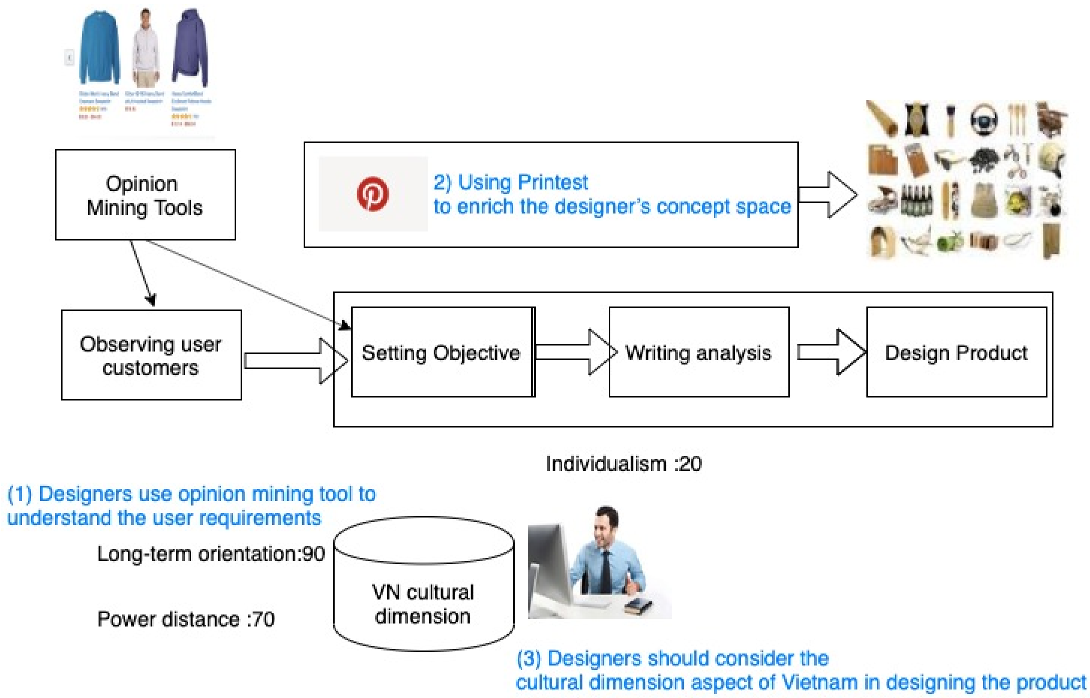


Figure 5.4: The proposed culture-oriented product design framework

5.3.2 Case Studies

This subsection will investigate the case studies as follows.

- Hypothesis 1: The first hypothesis aims at answering which user requirements would be suitable for culture-oriented product design according to various types of products

- Hypothesis 2: The second one will investigate which cultural attributes would be suitable for culture-oriented product design.

In order to do that we conduct an interview process as follows: We first collect a lot of amazon review documents which includes the customer reviews from various products categorized into two types of products including electronic and fashion products as follows.

- Electronic Products: phone, camera, vacuum, laptop, Phone cover, speaker

- Fashion Products: Bag and cases, Clothing, hat, skirt

The collected amazon reviews are mentioned in Chapter 4. After that, we perform the proposed system (we mentioned in Chapter 3 and Chapter 4, to obtain aspects and corresponding reviews. We select a set of customer reviews and their aspects and interview with the participation of designers from three countries: Vietnam, Japan, and China. The detail of designers are shown in Appendix. Since our work is mainly for product design and fashion design, so we select designers who have experience about product design and fashion design.

Table 5.1: Some Cultural Items in Vietnam, Japan, China

Cultural Word	Meaning
Calligraphy	Traditional wearing
Origami	Traditional items of Japan and it is popular
Ceramic, Porelain, Brown	in Traditional game of Vietnam
Paper engraving	Common in Vietnam, China, Japan
Traditional painting	in Vietnam, Japan, and China
Bamboo	traditional tree in Asian
Drum	traditional drum (i.e Dong Son drums in Vietnam)
Terraces	A traditional issue for ethnic people: In Vietnam
Traditional Flowers	A traditional follower for Vietnam, Japan, China
Stilt house	A house for ethnic people
Long dress	traditional dress: Ao Dai, Kimono, etx
Animation Items (panda, doremon, pikachu)	Animation Items are popular in Japan

For the purpose of being used user requirements with cultural attributes for product design, we consider various cultural attributes and used it along with user requirements for a product review, as shown in Table 5.1. The cultural attributes were selected based on the view points that they are popular items among three countries.

It is noticed that to make a product that is familiar with the culture of a country or a local group, the cultural items are important. Table 5.1 depicts some traditional elements in Vietnam, Japan, and China. For example, Origami and animation items are popular in Japan. Drum and Stilt houses and Long Dress (Ao Dai) are familiar with Vietnamese people.

Similar to Chapter 4, we interview 50 designers from Vietnam, Japan, and China. The condition for selecting designers is that the designer should have background on either product design or fashion design. Otherwise, they should have experience in designing products or they are senior designer. The information about designers is described in the Appendix. The following questions are mainly asked to verify the proposed framework.

- Question 1: Which cultural attribute can contribute to user requirements for product design?
- Question 2: How designers can design a new product/concept using the brainstorming method which combines cultural attributes with user requirements in culture-oriented product design?
- Question 3: What is the difference between designing electronic products and fashion products in terms of cultural aspects?

Each designer is also asked for choosing which cultural attributes are appropriate for combining with user requirements in designing a culture-oriented product. The designers are able to use the proposed framework as described in Chapter 3 and Chapter 4.

Figure 5.5 and Figure 5.6 shows how designers choose cultural attribute for being used with Fashion products and Electronic products. Figure 5.5 showed the corresponding of the percent vote with each type of product: Laptop, Camera, Speaker, Vacuum, and Phone. Figure 5.6 demonstrates the ratio of designers votes with each type of fashion product, including Skirt, Hat, Clothing, Bag, and Cover (i.e for mobile phone).

As the results indicated, "animation" is favorite for designers in terms of designing both electronic and fashion products. Traditional "Long dress" is not chosen much for designing electronic products. Interestingly, designers think that using "Drum" can make a benefit for designing a smart speaker. It seems designing the shape and/or the voice of a smart speaker related to the drum concept. It also indicated that "screen" is essential for mobile phone and the laptop. The "function" and "interface" are essential for being considered in the culture-oriented product design for phone and camera. Meanwhile, it is less important for designing a vacuum.

For fashion products, traditional painting, Flower, Animation, Calligraphy are competitive for designing fashion products. "Traditional painting" and "animation" are used much in all fashion products.

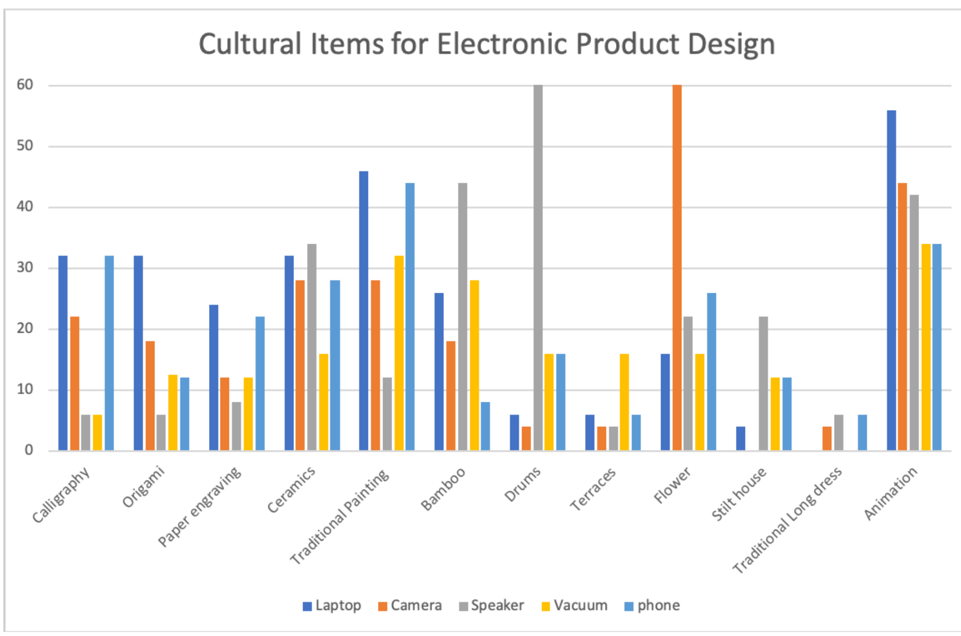


Figure 5.5: Designers vote for using cultural items with Electronic Products

Figure 5.7 depicts the results of user requirements extraction and how designers think it would be appropriate for the culture-oriented product design. We perform the system to obtain the list of keywords and a sentence corresponding with the keywords. We focus on considering the laptop product. The results showed that only the sentence 02 receiving not many votes from designers. There are 04 sentences receiving a high number of votes and 02 sentences obtained a medium number of votes. This results indicated that the proposed system would contribute to cultural oriented product design.

Also, we verify with designers about whether or not our framework can combine with

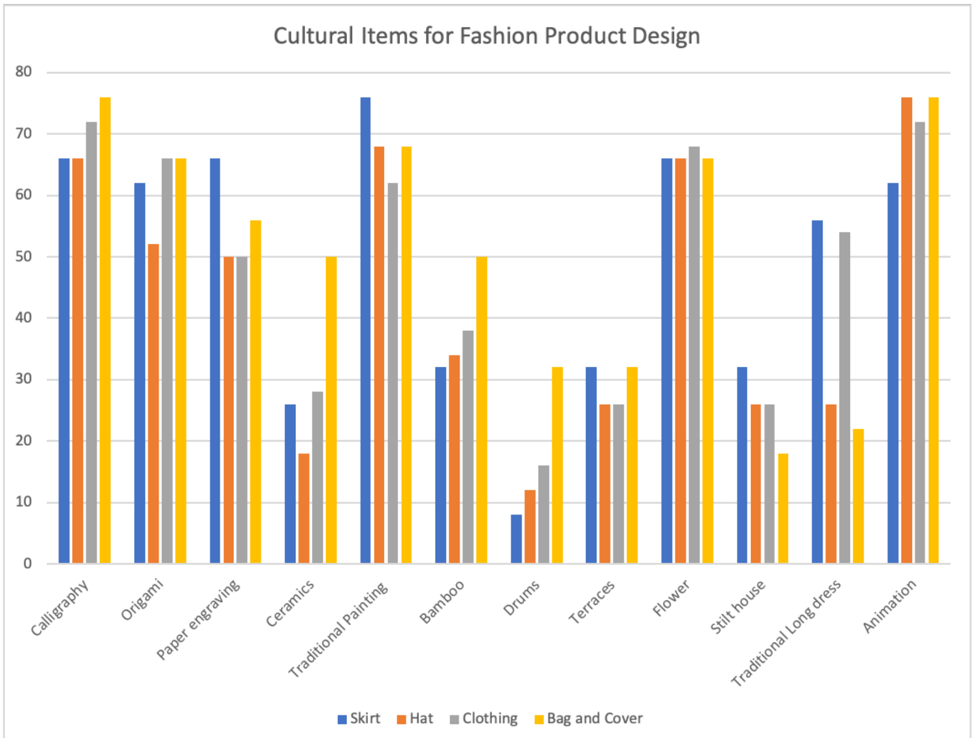


Figure 5.6: Designers vote for using cultural items with Fashion Products

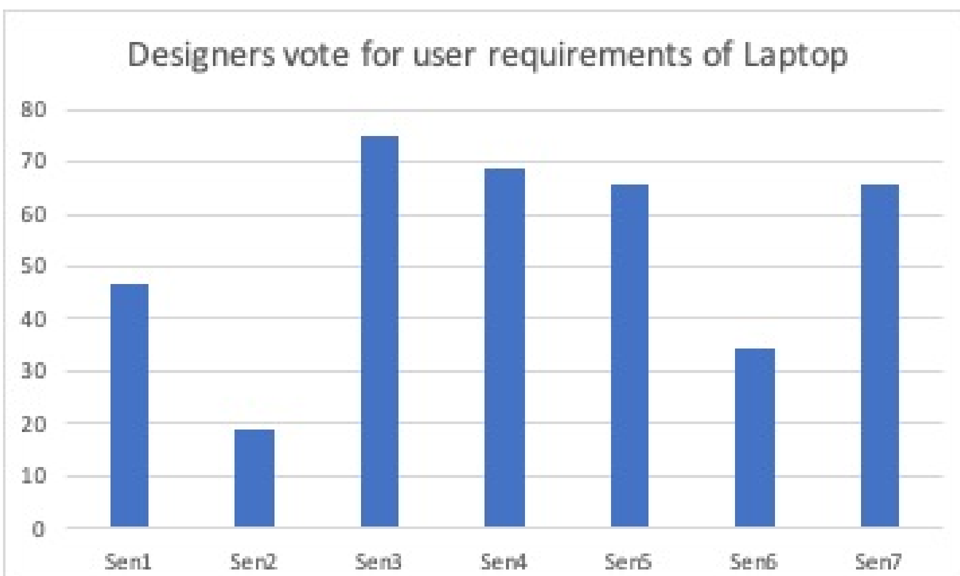


Figure 5.7: Designers vote for checking which outputs of the URs extraction with the Laptop

the Pinterest search for enriching the space of the user in designing a product. As shown in Figure 5.8, most designers agree that using Pinterest would support for product design.

We also check with designers about how the proposed framework can work with the combination of cultural attributes and user requirements. Figure 5.9 depicts that most designers consider that the combination of user requirements and cultural attributes contribute to culture-oriented product design.

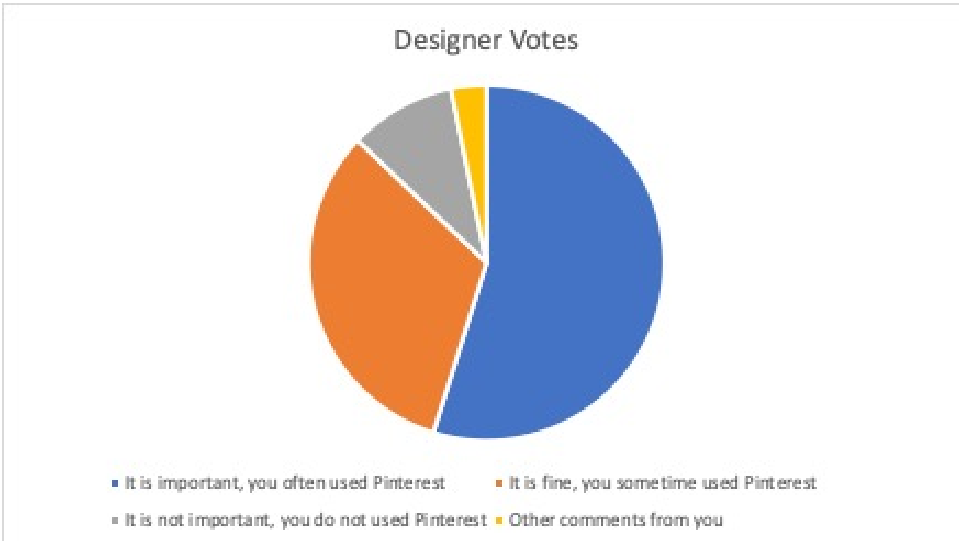


Figure 5.8: Designers vote for using Pinterest in the culture-oriented product design

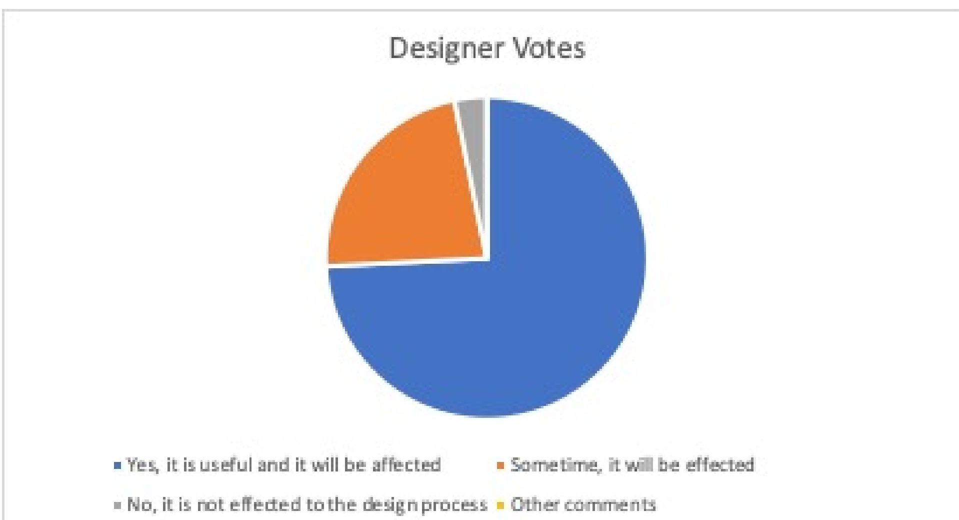


Figure 5.9: Designers vote for using the proposed framework with cultural-oriented product design

After verifying the appropriateness of the proposed framework, we conduct a brainstorming section to ask the designers for combining cultural items in designing product. Regarding the brainstorming process, the designers are divided into 10 teams in which the number of each team is 5 peoples. Figure 5.10 and Figure 5.11 highlight some results of the brainstorming process

Designer	**Brain Storming**
Using paper graving in handbag design, to design a handbag of winter.	The texture and the creases of the paper can be reflected in a handbag, and the synaesthesia of the paper and other crafts can also be used to show a feeling of snow.
Combining origami art with clothing	Combining origami art with clothing, different origami methods can show different styles of clothing.A garment is designed by folding without the aid of a needle or thread and folding allows for layers.
traditional painting to clothing	I will apply traditional painting to clothing. People will carry forward the traditional painting method by purchasing clothing and let more people know the profoundness of Chinese culture.
Origami art is like the three-dimensional structure in fashion design major	Origami art is like the three-dimensional structure in fashion design major, which can show the volume through folds. The methods and expressions in origami art can be applied to clothes, which can make clothes more diversified, more interesting and diversified.

Figure 5.10: Designers vote for using cultural items with Fashion Products

The brainstorming results suggested that one can use "paper engraving" in handbag design. The use of origami and traditional painting can also be helpful in designing clothers.

Designer	Brain Storming
Utilizing the characteristics of bamboo	Utilizing the characteristics of bamboo joints, it can be considered to design the long vacuum tube to be retractable. Applying the art of origami can design the vacuum cleaner into a foldable type for easy storage and save space. Some other cultural elements, such as calligraphy, traditional painting, flowers, etc., can be used for external decoration of the product, sprayed on the surface of the product.
Using ceramic and bronze	Using ceramic and bronze (or cloisonne) as the main material for the design of the laptop, through the performance of materials and color interpretation of the performance of traditional Chinese culture, technology products in the traditional form to show.
Using bamboo	In Chinese culture, bamboo represents the humility of a gentleman. Combining bamboo with cultural and creative products can not only produce cultural and creative products for wearing, but also combine solid materials of bamboo with electronic products. For example, the bamboo computer shell not only meet the cultural needs, but also makes the computer's heat dissipation better.

Figure 5.11: Designers vote for using cultural items with Electronic Products

Another interesting concept is to use the Bamboo with Vacuum tube in terms of retractable. In addition, the use of origami technique can be designed the vacuum cleaner into a fold-able type for easy storage and save space. The designers suggested that we can use ceramic and bronze as the main material for the design of the laptop. It can keep the traditional of Chinese for making the product more friendly with users.

5.3.3 Some concepts: Cultural-oriented Product Design

Regarding to Vietnamese cultural design, we select some traditional attributes which are described in Table 5.2.

Table 5.2: Some Vietnamese cultural words

Cultural Word	Meaning
AoDai	Traditional wearing
Bamboo	traditional tree
Lotus	image flower of Vietnam
Dong Son drum	image drum of Vietnam
Color	colour
terraces	A common issue for ethnic people in Vietnam
Stilt house	A house for ethnic people in Vietnam
Buffalo	A house for ethnic people in Vietnam
Hoa Mai	A traditional follower for south of Vietnam
Hoa Dao	A traditional follower for Vietnam
Chu Teu	in Traditional game of Vietnam

We asked designers who create computer logos and banners and people who design clothing, and they all had the same opinion that the Vietnamese culture is an influence in product design for Vietnamese products. However, in their opinion, there are some products in which the influence is not as clear. Usually, those products are imported from foreign countries and are in the high technology sector, such as mobile phones and computers. If Vietnamese culture would be considered when designing products, the products would be more attractive and Vietnamese people would accept them more easily.

Beside that we conduct another experiment to check the creativity of designers when considers the cultural aspect from Vietnam. We list some cultural items and its descriptions and ask designers for making a brainstorming about designing a product which utilize the proposed framework (Vietnamese cultural dimension is able to consider).

The first combination is to use the concept "AoDai" and "Dong Son Drum" to find an appropriate concept for designing cultural oriented product. One designer used the logo symbol in "Dong Son" drum in Aodai to make it more attractive for local person.

The second combination is used the "shape" of Dong Son drum to design a key box. It makes a box more friendly with users. Another item is also selected as designer in our product is the use of Bamboo including (level, bamboo) for fashion design. It can be also referred to the design of "Minh Hanh"- Winter 2014.

We also investigate the prototyping design task by asking designers using cultural dimension with Vietnamese cultural items including: "Hoa Sen (Lotus)", "Ruong Bac Thang(terraces)", "Trong Dong (Drum)". We ask the designers team to conduct the process as follows. Given the list of Vietnamese cultural items and we explain for them about the meaning of Vietnamese cultural dimension, we start to let designers use the

Pinterest tool to support the designing process. As a result, we have very nice collection of design items as shown in the following figures (from figure 5.12 to figure 5.13).

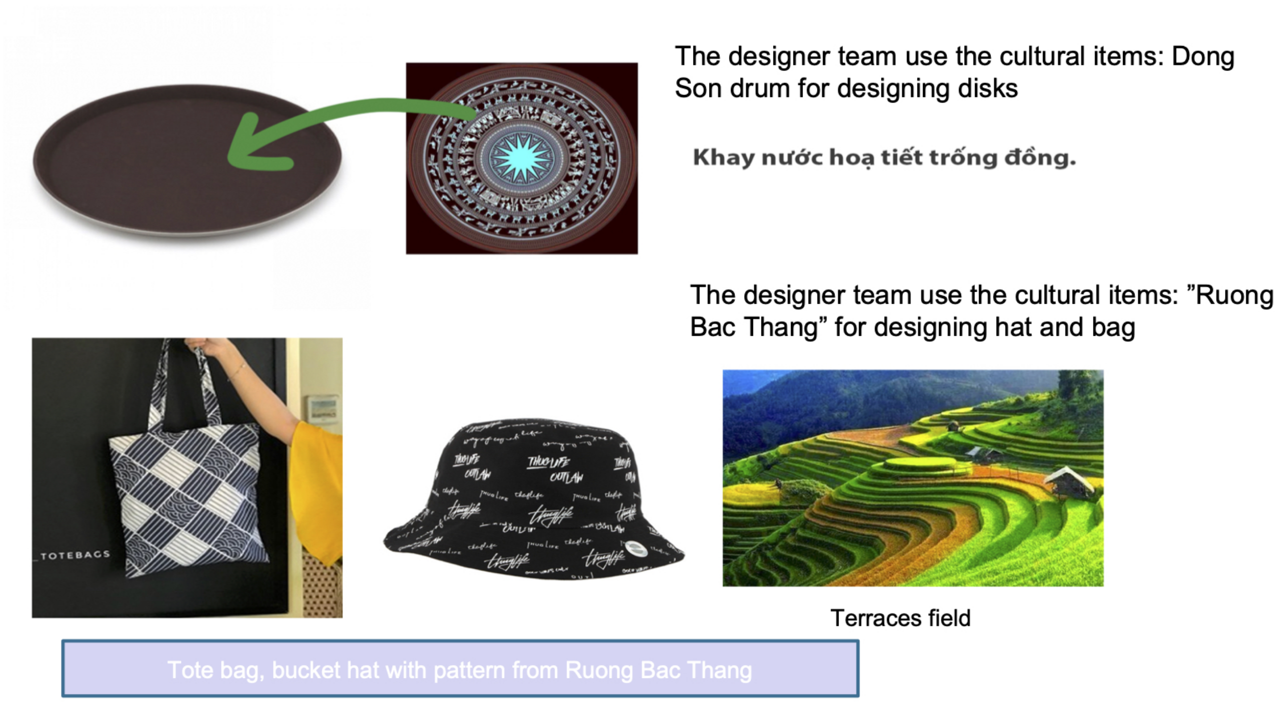


Figure 5.12: Using Vietnamese Cultural for Product Design

Figure 5.12 showed that the designer team would use the cultural item with Dong Son drum for designing disks with vignettes. The use of terraces can be use for designing hat and bag. These items are suitable for Vietnamese local people as well ask making attractive to visitors and tourists.

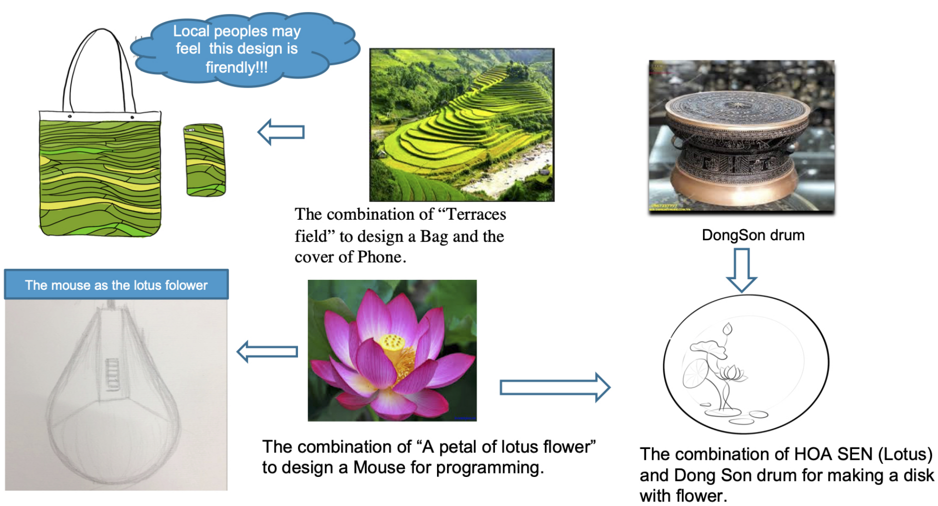


Figure 5.13: Using Vietnamese cultural aspects for product design

Figure 5.13 shows some concepts being created by designers. The bag and cover of the phone with vignettes of terraced fields and the mouse with shape of a petal of lotus flower.

5.4 Summary of the chapter

In this paper, we have presented a study on the integration of cultural aspects and user requirements in culture-oriented product design.

We listed several products using culture in their product design. We also defined the relationship between culture and design. Furthermore, we demonstrated the relationships between culture and product design concerning the orientation of users (the customers voice). Finally, we did some case studies that indicate that cultural aspects are essential components in product design. We checked the contribution of cultural attributes and user requirements with designers from Vietnam, Japan, and China to verify that the proposed framework is effective. Moreover, it would help designers in creating and designing new products. Finally, an investigation of the influence of Vietnamese culture on some product development cases was outlined in this paper. These cases demonstrate that Vietnamese culture has a significant influence on the development of products. Results from our interviews with designers showed that our proposed framework is useful.

Chapter 6

Conclusion and future work

This thesis presents a study on extracting user opinion on the internet and its application for product design. The key problem is that we focus on utilizing information from online customer reviews by performing opinion mining techniques to extract user requirements. As we have presented in the thesis, we exploited various information of customer reviewers on the website, including top reviews, helpful reviews, keywords, and concepts about the product. The user requirements are defined as a set of aspects of products and their corresponding opinions. We apply opinion summarizing techniques to extract user requirements and used it for supporting designers in terms of product design. Regarding the technical point of views, we obtain the major contributions as follows.

- We conduct various machine learning models including conventional machine learning and deep learning for helpful identification problems. We showed that BERT attained the best performance while the simple method like CNN models can also be used in some situations. We also verify the XGBoost and SVM for helpful reviews identification problem.

- We conduct empirical experiments for sentiment classification with the Amazon dataset and showed that BERT text classification achieved the best performance. The Fasttext model achieved a competitive result but its training and testing time are much faster than other models (except SVM).

- We work on unsupervised methods for aspect recognition and supervised learning using the state of the art deep learning models. Experimental results showed that BERT and GCDT would help to achieve the competitive with the sate of the art performance in benchmark data. We further perform these models on electronic data and see that it can achieve very promising results.

- We investigate many texts summarizing techniques for summarizing customer reviews. We then illustrate that using the BERT similarity score would help to obtain a better summarization result for customer reviews.

Regarding the perspective of design contribution, we achieve the following issues as follows.

- Our case studies showed that the framework is effective and useful for designers when the designer conducts an early phase of product design.

- We interview with designers to see which information they need in terms of designing products. The results showed that the proposed helpful identification model, top reviews, and aspect extraction contributed much to the process of designing products. We further investigate the case study with electronic and fashion products to understand which aspects designers take priority. This qualitative analysis will benefit for the process of designing products.

We also study the influence of cultural aspects for product reviews in terms of designing products. We have presented a study on the cultural role of product design. We listed several products using culture in their product design. We also provided a definition of the relationship between culture and design. Furthermore, we demonstrated the relationship between culture and product design with respect to the orientation of users (the customer's voice). Finally, we did some case studies to indicate that cultural aspects are essential components in product design. These cases demonstrate that cultural attributes have a great influence on the development of products. Results from our interviews with designers showed that our proposed framework could support designers in an effective way to understand user needs. Last but not least, our recommendation for supporting designers in product design can be summarized as follows

- Extracting user requirements using helpful reviews, keyword extraction, sentiment classification, and opinion summarization. This tool would provide useful information for designers.

- Focusing on the top rank of customer reviewers as important source for product design. Top customer reviews have meaningful information for designers in terms of designing products.

- Cultural attributes are appropriate for designers in designing a product. Especially, integrating them with opinion mining would bring many benefits for product design.

Finally, our research has a promising contribution in knowledge science when we consider tacit knowledge as user requirements and it is transformed to explicit knowledge from designers.

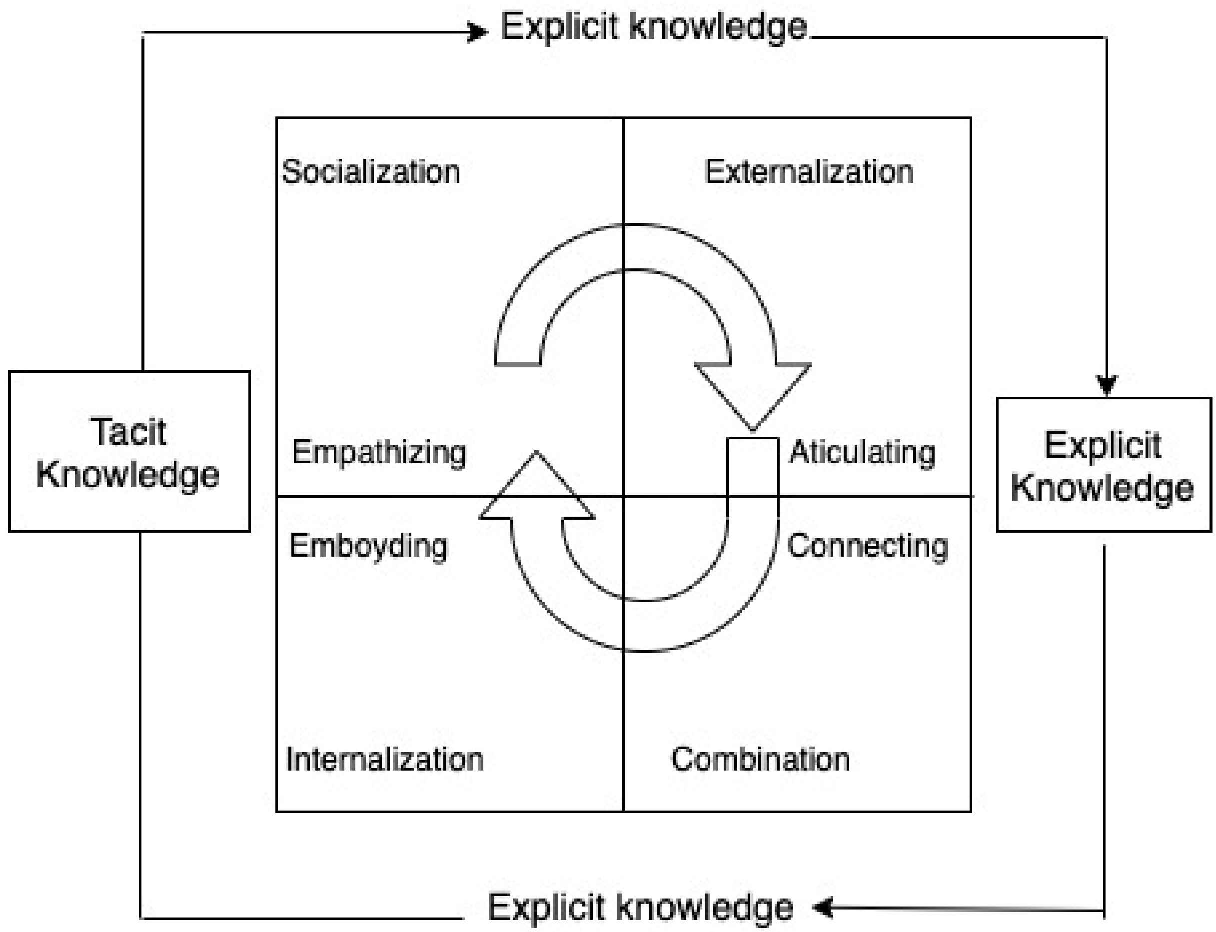


Figure 6.1: The SCICE framework in knowledge science. The SECI model is a well known conceptual model that was first proposed by Nonaka (1991 and expanded by Nonaka and Takeuchi, 1995). It describes how explicit and tacit knowledge is generated, transferred, and recreated in organizations.

Our contribution to finding frameworks that utilize Computer Technology to support Knowledge Science is described as follows. It transfers the users knowledge into designers knowledge enrich knowledge space following the SECI model of knowledge dimensions (Nonaka) by using modes of knowledge conversion tacit to tacit, tacit to explicit, explicit to explicit knowledge for designers, explicit to tacit to generate ideas, concepts in designing a novel product for our future society. The explicit knowledge is user requirements, which are extracted from online customer reviews by the proposed user requirement extraction model. Tacit knowledge is related to the expertise of designers. The process of extracting online reviews to obtain user requirements (top review, helpful reviews, aspects, summary) is related to the process of explicit to explicit knowledge for designers. The designers transform tacit knowledge to implicit knowledge which can be used for creating new concepts in product design. In addition, the proposed framework can allow designers working together to create new concepts by working together - which means the process of transfers tacit to tacit knowledge among designers.

In future work, we would like to improve the performance of our current opinion summarizing the system and extend it to a different language other than English. The following points we would like to study as follows. We will improve the performance of each component within the frameworks, including top review identification and helpful review detection. We also would like to extend our sequence learning based on aspect extraction with unlabeled data, which can be largely collected. Text summarization is essentially required for being used with higher performance.

In the future, we will study how to build a framework for different languages than English. This can be easy for taking different cultural aspects in a culture-oriented product design. We also want to build a model for dealing with review comments on social networks such as Twitter and Facebook.

In future work, we would like to investigate other information than text from customer reviews (i.e., Video and Voice), and we expect that extracting culture factors from the only review documents would be feasibly using in our product design. We also would like to exploit our framework into a real design process and evaluate how they work in the design process. One of the possibility for extending our work is to exploit our model for other similar type of designs where we can assess a large scale of customer online reviews. For this reason, we would like to apply our framework for service design where we can extract user requirements from online customer reviews in online services such as Trip-Advisor, Expedia, and Booking.com. In addition, the service design would be applicable for taking into account cultural attributes which are key factors for satisfying customers coming from different culture (i.e different countries, different province, etc). Some recent works have been indicated that one can utilize Hofsteds model of cultural dimension for improving service design. For example, this model is used in Booking.coms designer team [84] which considers Individualism score for Brazilian market to change the interface. Hofsteds model of cultural dimension is also used for designing the behavior of Cortana (Microsoft Assistant - it is similar to Google home's assistant). Regarding to this point, in our future work we would like to consider the use of Cultural dimension along with the proposed framework for service design.

Chapter 7

Appendix: Questionnaire

This chapter will show the questioners used in our research and some real case of cultural oriented product design.

7.1 Questioners using in interviewing designers

7.1.1 Questioner I: Chapter 3

Question about Product

Please answer your opinions when you read customer reviews from the top reviews and the normal reviews. Please give us the feedbacks about your opinion.

1. Question1. Do you agree that the information from top reviews are more informative than normal reviews?

   Mark only one oval.

   - Strongly agree
   - Agree
   - Not agree
   - I do not know

2. Question 2. Do you agree that the information extracted by helpful review are informative for product design?

   Mark only one oval.

   - Strong agree
   - Agree
   - Not agree
   - I do not know

3. Question 3. Do you agree that top review has informative information for product design?

   Mark only one oval.

   - Strongly agree
   - Agree
   - Not Agree
   - I do not know

4. Question 4. Top positive reviews contain informative information for product design

Mark only one oval.

- Strongly Agree
- Agree
- Not Agree
- I do not know

5. Question 5. Top critical reviews contain important information for designers?

Mark only one oval.

- Strongly agree
- Agree
- Not Agree
- I do not know

6. Question 6. Top critical reviews contain more information information than top positive reviews for designers?

Mark only one oval.

- Strongly Agree
- Agree
- Not Agree
- I do not know

Table 7.1: The list of designers

ID	Country	Gender	Age	Background	Experience	Designer Type
001	China	Female	20	Dalian Polytechnic University	03	Product-Design
002	China	Female	20	Dalian Polytechnic University	03	Product Design
003	China	Female	21	Dalian Polytechnic University	03	Product Design
004	China	Female	20	Dalian Polytechnic University	03	Product Design
005	China	Female	22	Dalian Polytechnic University	03	Product Design
006	China	Male	20	Dalian Polytechnic University	03	Product Design
007	China	Male	23	Dalian Polytechnic Universityy	03	Product Design
008	China	Male	22	Dalian Polytechnic University	03	Product Design
010	China	Female	22	Dalian Polytechnic University	03	Product Design
011	China	Female	22	Dalian Polytechnic University	03	Product Design
012	China	Female	22	Dalian Polytechnic University	03	Product Design
013	China	Female	22	Dalian Polytechnic University	03	Product Design
014	China	Female	22	Dalian Polytechnic University	03	Product Design
015	China	Male	24	Dalian Polytechnic University	03	Product Design
016	Vietnam	Male	23	Hue University College of Arts	03	Fashion Design (Art)
017	Vietnam	Female	22	Hue University College of Arts	03	Game Design
018	Vietnam	Female	28	Hue University of Science	03	Fashion Design
019	Vietnam	Male	29	Hue University College of Arts	03	Fashion Design
020	Vietnam	Female	30	Hue University of Science	03	Fashion Design
021	Vietnam	Female	27	Hue University of Science	03	UI/UX design
022	Vietnam	Female	30	Hue University of Science	03	Game Design
023	Vietnam	Female	32	Multimedia Arena	08	Fashion Design and Game design
024	Vietnam	Female	29	Vinh University	05	Fashion and House Design
025	Vietnam	Female	38	Thai Nguyen University	12	Fashion and House Design
026	Vietnam	Female	38	Foreign Trade University	03	Fashion Design
027	Vietnam	Female	39	National Economics University	5	Fashion Design
028	Vietnam	Male	41	Hue University of Science	18	interior designer
029	Japan	Female	42	Japan Advanced Institute of Science and Technology	06	Fashion Design
030	Japan	Female	30	Japan Advanced Institute of Science and Technology	03	Product Design
031	Japan	Male	43	Japan Advanced Institute of Science and Technology	05	Product Design
032	Japan	Male	40	Japan Advanced Institute of Science and Technology	06	Product Design
033	Japan	Female	40	Japan Advanced Institute of Science and Technology	08	Architecture Design
034	China	Male	24	Dalian Polytechnic University	03	Product Design
035	China	Female	21	Dalian Polytechnic University	03	Product Design
036	China	Male	21	Dalian Polytechnic University	03	Product Design
037	China	Male	21	Dalian Polytechnic University	03	Product Design
038	China	Female	21	Dalian Polytechnic University	03	Product Design
039	China	Female	21	Dalian Polytechnic University	03	Product Design
040	China	Female	23	Dalian Polytechnic University	03	Product Design
041	China	Female	20	Dalian Polytechnic University	03	Product Design
042	China	Female	20	Dalian Polytechnic University	03	Product Design
043	China	Female	20	Dalian Polytechnic University	03	Product Design
044	China	Female	22	Dalian Polytechnic University	03	Product Design
045	China	Female	22	Dalian Polytechnic University	03	Product Design
046	China	Female	21	Dalian Polytechnic University	03	Product Design
047	China	Male	23	Dalian Polytechnic University	03	Product Design
048	China	Male	22	Dalian Polytechnic University	03	Product Design
049	China	Male	23	Dalian Polytechnic University	03	Product Design
050	China	Female	22	Dalian Polytechnic University	03	Product Design

7.1.2 Questioner II: Chapter 4

Questionnaire 1

1. Are presented user requirements about Functions of the product informative for design? Yes ☐ No ☐

2. Are presented user requirements about Shape of the product informative for design? Yes ☐ No ☐

3. Are presented user requirements about Content (Software) of the product informative for design?

Yes ☐ No ☐

4. Does the features list provide useful information for designers to improve product and develop product?

Yes ☐ No ☐

5. Does the method save time for designers in collecting user requirements for product design? Yes ☐ No ☐

6. Do performed opinion extractions of reviews enrich design knowledge? Yes ☐ No ☐

7. Which components in the method are significant for improving product and developing product?

---

8. Does "Advantage – Disadvantage" list help designers in designing product? Yes ☐ No ☐

9. How do you evaluate usefulness of the presented information of user requirements for further design?

Figure 7.1: Questionnaires for designers

7.1.3 Questioner for culture oriented product design

An interview survey for cultural oriented product design

This questionnaire is evaluating the use of automatically extracted user requirements. They represent the opinions of the users of the real products. It is intended for use by product designers in further improvements and development of products.

Q1. Have you ever used the opinion of user customers in Amazon and other online shopping to support for product design. If not, do you think it is important?

[ ] very often
[ ] often
[√] Some times
[ ] Never
[ ] I do not know
[ ] Other

Q2. When you design an electronic item, could you let us know which components are most important (please rank according to the priority of important): Screen, memory, shape, quality, speed)

Answer: quality; speed; memory shape; screen

Q3. When you design a fashion product, how cultural aspects can make influence to the design process?

Answer:In the design process, cultural factors affect the product appearance, color, use and so on. In some places people pay attention to the appearance of the product, in others they pay attention to the quality of the product.

Q4. Would you let us know the difference of cultural aspects in terms of product design? Could you let me know how it is important?
Answer: color texture function quality

Q5. Which features can combine with cultural items for fashion product?

	bag	skirt	hat	clothing	Phone cover
sharp	√	√	√	√	
color	√	√		√	
texture	√	√	√	√	
Light weight	√	√			
thin	√				√

Your suggestion					

Q6. which user requirements can combine with cultural aspect for electronic product?

	phone	camera	vacuum	laptop	Phone cover	speaker
sharp	✓	✓				
screen	✓					
Battery life				✓		
color		✓				
function	✓		✓			
Interface						
Light weight			✓		✓	✓
Your suggestion						

Q7. Please see the <u>user requirements</u> as keywords in the table, and let us know which would contribute to the cultural product? (for fashion product)

Sentences	Bag and cases	Clothing/hat/skirt
S1. The pink flowers look really fake and cheap.		✓
S2. The plastic handles cannot stand up to normal wear	✓	
S3. Hat for Halloween is excellent		✓
S4. The size is too big for fitting with us	✓	
S5. Using the color suitable in the new year are good idea		✓
S6. This item is not suitable with older person.	✓	
S7. The quality of the clothing is too bad with very hot weather		✓

Q8. Which user requirements can combine with cultural items for designing electronic product? (Please mark on the box)

Sentences	laptop	camera	speaker	vacuum
S1. Some features are not friendly (volume wheel, sound quality, etc.)			✓	
S2. The camera's picture quality under bright light is very poor.		✓		
S3. The keyboard is too slick.	✓			
S4. I especially like the backlit keyboard.	✓			
S5. The battery doesn't last long but I'm sure an upgrade battery would solve that problem.	✓			
S6. Maximum sound isn't nearly as loud as it should be.				✓
S7. I really like the feature of the app (no go zones, room division, virtual walls)	✓			
I am pleased with the fast log on, speedy WiFi connection and the long battery life (>6 hrs)				

Q9. In terms of designing cultural oriented product, which cultural items in your country are suitable with the following products, to design cultural-oriented product. (You are provided user requirements by assessing the framework)

	laptop	camera	speaker	vacuum	phone	skirt	hat	clothing	Bag and cover
Calligraphy						✓	✓	✓	✓
Origami	✓					✓	✓	✓	✓
Paper graving						✓	✓	✓	✓
Ceramics, Porcelain, Bronze	✓	✓			✓				✓
Traditional painting						✓	✓	✓	✓
Bamboo	✓	✓	✓				✓		✓
Drums			✓		✓				
terraces									
Flower (national)						✓	✓	✓	✓
Stilt house									
Long dress						✓		✓	
animation items (panda, doremon, pikachu, etc)	✓	✓	✓	✓	✓		✓		✓

Q10. How do you think about the importance of using Pinterest in the cultural oriented product designs and Product Design?

[ ] It is important, you often used Pinterest

[✓] It is fine, you sometime used Pinterest

[ ] It is not important, you do not used Pinterest

[ ] Other comments from you.

Q11. When you design a product (concept), if you are providing a lot of user requirements and similar items to that product, do you think it will be helpful for you? If so, how it can be influence to your design process?
(You are provided user requirements by assessing the framework)

[✓] Yes, it is useful and it will be affected

[ ] Sometime, it will be effected

[ ] No, it is not effected to the design process

[ ] Other comment from you

Q12. Assume that you will use traditional cultural items (See the table below), could you use it for making a design concept for a cultural oriented product?
[The product for making a concept would be]

laptop	camera	speaker	vacuum	car	skirt	hat	clothing	Bag and cover

(If it is possible you can use 30-50 minutes to make a concept)

Some traditional cultural items
Calligraphy Origami Paper graving Ceramics, Porcelain, Bronze Traditional painting Bamboo Drums terraces Flower (national) Stilt house Long dress animation items (panda, doraemon, Pikachu, etc.)

Combining origami art with clothing, different origami methods can show different styles of clothing.A garment is designed by folding without the aid of a needle or thread and folding allows for layers.

7.2 Some example about cultural aspects in Product Design

7.2.1 Boutique design

A new trend towards modern design with a distinctly Vietnamese style, using locally sourced craftsmanship, is creating new opportunities for both manufacturers and designers in Hanoi. One design store that has witnessed this change first-hand is YNOT Design (1/22 Nghi Tam Village, Tay Ho) located in Tay Ho, Hanoi. YNOT is renowned for its glossy and brightly colored furniture. The company mainly procedures they products by using local bamboo and traditional techniques, which are popular both in Vietnam and abroad. Bamboo is considered one of the cultural trees of Vietnam. The products using bamboo can transfer this message to foreign consumers; it also suggests a friendly environment for Vietnamese people when they use products made with bamboo. Figure 7.2 shows how bamboo can be used in design, including many items of home furniture.

Figure 7.2: Vietnamese culture: Bamboo in design: @The Rise of Design Boutiques in Hanoi

7.2.2 Fashion in Vietnam

One of the areas we would like to investigate regarding how Vietnamese culture contributes to product design is in fashion design. Fashion in Vietnam has been changed rapidly along with the development of society. Customers require the essence of culture to be expressed in designing clothes. In addition, more than 90 brands would like to enter the Vietnamese youth market, so they should design and adapt their style to Vietnamese culture. One example of Vietnamese fashion is the Vietnamese traditional garment, the

Ao Dai, perhaps the most interesting example of the influence of Vietnamese culture. Many modern designers have innovatively updated the Ao Dai (long dress) to reflect the youthfulness and color of modern culture. Figure 7.3 shows some examples of the modern Ao Dai, which considers both Vietnamese culture and the dynamic tastes of the youth market. When considering how Ao Dai can be suitable for foreign consumers, many Ao Dai styles are easily adaptable to other cultures.

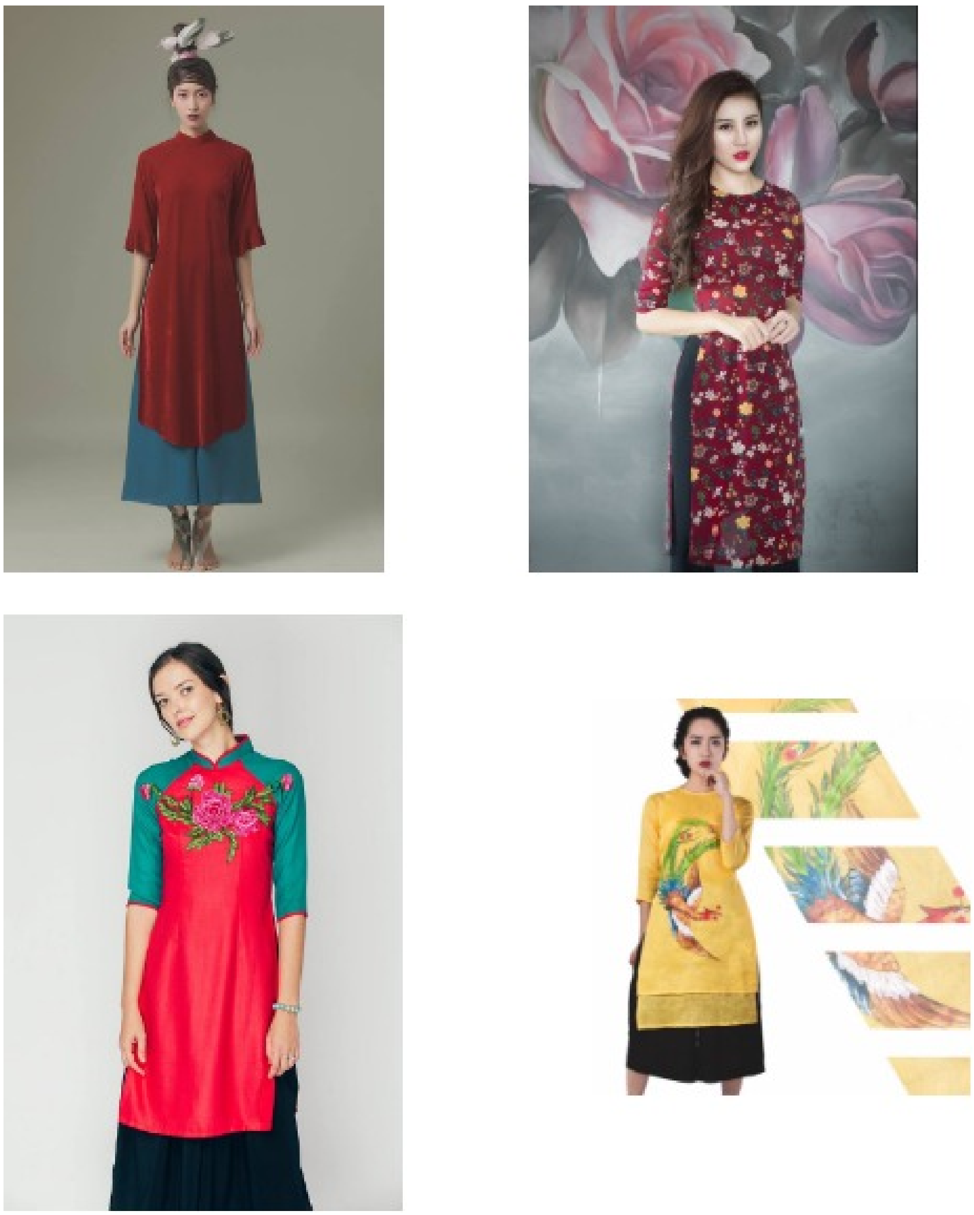


Figure 7.3: Vietnamese culture: Modern AO DAI design

The Landmark Tower

The design of the landmark building is based on the Ao Dai concept, a design unique to Vietnam. The buildings form is designed using bold vertical lines flowing upwards, reaching up to the sky as a representation of Vietnams growing influence in Asia. The tower is a reminder of indigenous design. Observing the landmark, one can easily recognize that it is very attractive and compatible with Vietnamese culture. I think using the concept of Ao Dai in terms of designing buildings is an excellent idea, and can be applied to the design of many similar products.

7.2.3 VinFast car: The Vietnamese car

Recently, a new Vietnamese brand of car was established. The company develops many types of cars that are closer to Vietnamese culture while making sure that the cars obey international standards. Figure 7.4 illustrates some new concepts for designing Vietnamese cars with a consideration for Vietnamese culture. First, the design of the SUV TRN 02 by Torino is designed to be youthful and energetic with a stylized grille recalling terraced fields, showing that they understand the psychology and taste of Vietnamese consumers. In the TRN 01 model, Torino tried to incorporate the image of soul ethnicity into the nose of the car, echoing the brocade cloth made by ethnic minorities in Vietnam. In addition, the design for the TRN 03 sedan, which carries young lives, is inspired by the image of a traditional Vietnamese fishing boat. The VinFast sedan and SUV, designed in Pininfarina, Italy, even has the logo V (for Vietnam) nestled in the grille. This logo is not too iconic or deeply hidden, forging a link with simple psychology, making it easy to understand how much a car logo can reflect the aspiration of Vietnam.

Figure 7.4: Designing Vietnamese car with respect to the Vietnamese culture

Chapter 8

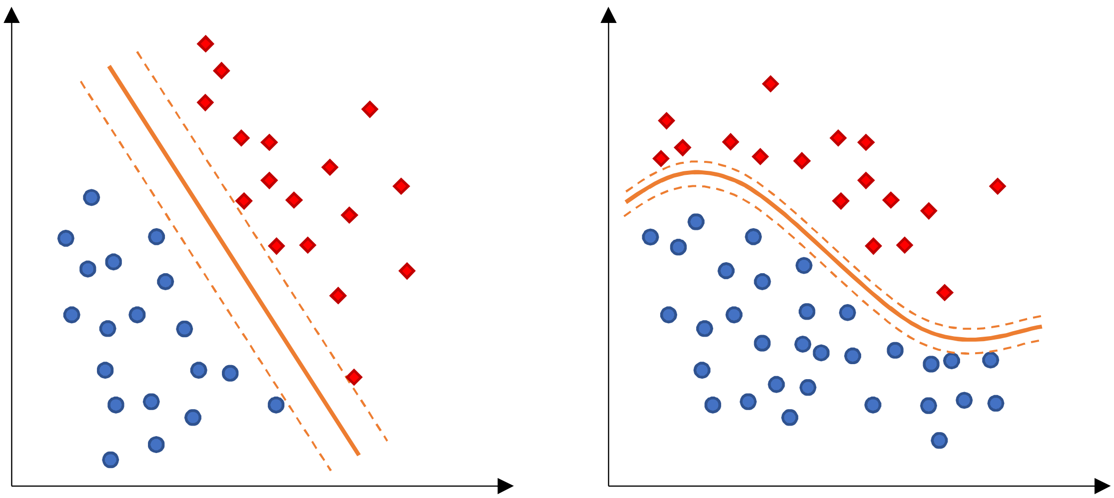
Appendix: Machine Learning Models

In this chapter, a summary about machine learning methods is presented. These methods have been used in extracting users requirements method described in previous chapters.

8.1 Machine Learning Models

8.1.1 Support Vector Machine

Support Vector Machine (SVM) is a supervised learning model that was originally developed in [79] and has been widely used as a strong baseline machine learning model for many classification problems in text mining. This model is typically applied for text classification because it can tackle the sparseness problem as well as large dimensional representation of text. The main idea of SVM is to learn a hyperplane in a high dimensional vector space to separate the classes. The hyperplane is a class separator as shown in Fig. 8.1. A hyperplane can be can be either linear or non-linear. To perform non-linear separation, a *kernel trick* technique is applied, which maps the input into a higher dimensional space. In the higher dimensional space, a hyperplane is then constructed for classification.



Linear **Non-linear**

Figure 8.1: SVM with linear and non-linear separators.

Formally, we denote a set of n training examples $\mathbb{S} = \{(x_1, y_1), (x_2, y_2), ..., (x_n, y_n)\}$, where $x_i \in \mathbb{R}^d$ is the input and $y_i \in \{-1, 1\}$ class label corresponding with x_i. Let $K : X \times X \to \mathbb{R}$ be a *kernel function* such that:

$$\forall x, x' \in X, \quad K(x, x') = \langle \Phi(x), \Phi(x') \rangle$$

with $\Phi : X \to H$ be a mapping of the input $x_i \in X$ into the higher dimensional space H. The hyperplane can be determined as:

$$w^T x + b = 0$$

with $w \in H$ and $b \in \mathbb{R}$. The hyperplane divides the space H into two sides corresponding with $y = -1$ and $y = +1$. Intuitively, there are many possible hyperplanes for separating data. We would like to find a good separator which has a largest possible distances to the closest training data points from each classes. This was because it generally can decrease the chance of separation error when applying to unseen data. The learning problems can be considered as finding a hyperplane with maximize margin. The closest training data point for each classes can be considered as support vectors. It is fortunately, we can apply quadratic programming to slove this global optimization problem. [27].

To avoid overfitting when dealing with noise data, a slack parameter ξ_i, i.e. a soft margin, can be applied for allowing some data points to reside inside of the margin. The objective function of SVM is defined as follows:

$$\min_{w,b,\xi_i} \frac{\|w\|^2}{2} + C \sum_{i=1}^{n} \xi_i$$

subject to:

$$y_i(w^T \Phi(x_i) + b) \geq 1 - \xi_i$$

$$\xi_i \geq 0$$

for $i = 1, ..., n$, and $C > 0$ is the trade-off between the maximum width of the margin and the generalization level of the separator, i.e. tolerant amount of data points inside the margin. Lagrange multipliers can be applied for solving the optimization problem. After that, the class of a sample point x can be determined through the decision function:

$$f(x) = (\sum_{i=1}^{n} \alpha_i y_i K(x, x_i) + b$$

with α_i are Lagrange multipliers.

8.2 Deep Learning

Deep Learning has achieved state-of-the-art performance in a wide range of tasks in Artificial Intelligence. This section will present fundamental issues about Deep Learning and its extension.

8.2.1 Deep Feed forward Neural Network

In the first subsection, we would like to present a Deep Feed forward Neural Network which is the basis models for Deep Learning. The goal of learning is to estimate some function $f(\cdot)$ that is used for predicting the values $\hat{\mathbf{y}} = f(\mathbf{x}; \boldsymbol{\theta})$ given input data $\mathbf{x}$ where $f(\cdot)$ is parameterized by $\boldsymbol{\theta} = (\theta_1, \theta_2, ..., \theta_k)$. The network needs to learn the value of $\boldsymbol{\theta}$ to minimize the loss function loss($\hat{\mathbf{y}}$,$\mathbf{y}$) between the prediction and the target y. Deep Neural Network used many perceptrons for training. A *perceptron* can map an input $\mathbf{x} = (x_1, x_2, ..., x_n)$ using a linear transformation or non-linear transformation as follows.

- A linear transformation can be defined as

$$m = \sum_{i=1}^{n} w_i x_i + b \tag{8.1}$$

  where $\mathbf{w} = (w_1, w_2, ..., w_n)$ are *weights* and b is a *bias.*

- A non-linear transformation using a differentiable, non-linear *activation function* $h(\cdot)$

$$z = h(m) \tag{8.2}$$

Fig. 8.2 depicts a single perceptron in which the activation function depending on the nature of training data as well as the distribution of target variable $\mathbf{y}$ [**?**]. We can list some popular activation function as follows

- Sigmoid:

$$\sigma(x) = \frac{1}{1 + e^{-x}}$$

- Hyperbolic tangent:

$$tanh(x) = \frac{e^x - e^{-x}}{e^x + e^{-x}}$$

- Softmax:

$$softmax(\mathbf{x}) = \frac{e^{x_i}}{\sum_{j=1}^{N} e^{z_j}} \text{ for } i = 1, ..., N \text{ and } \mathbf{x} = (x_1, x_2, ..., x_N) \in \mathbb{R}^N$$

Rectifier:

$$rec(x) = max(0, x)$$

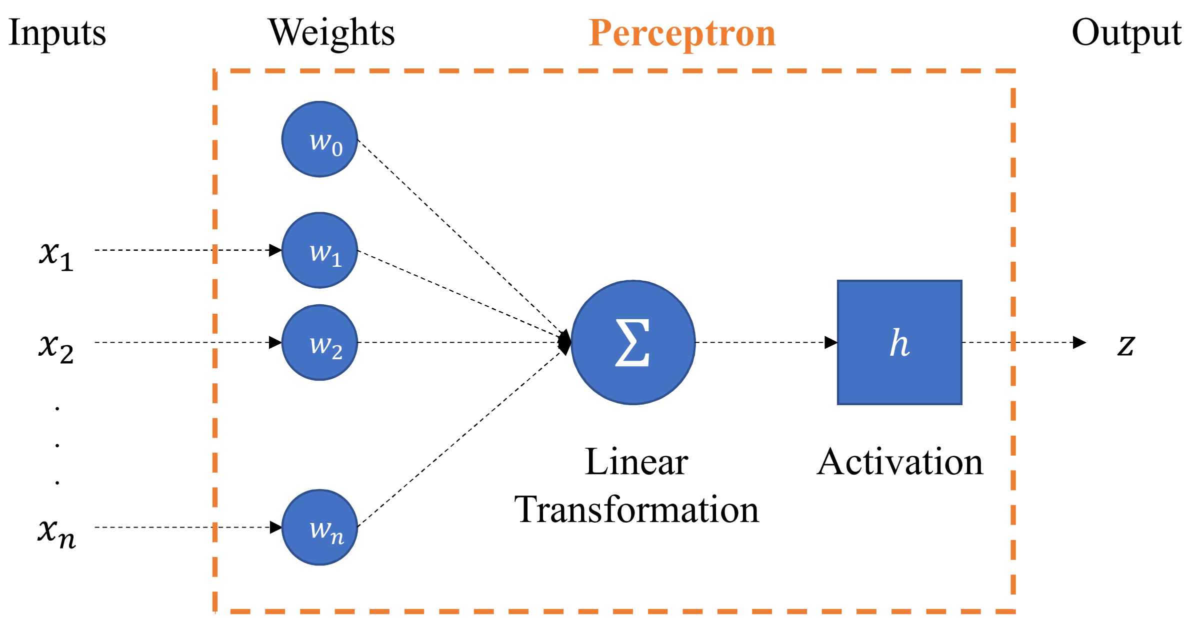


Figure 8.2: An illustration of of a perceptron

A Deep Feed forward Neural Network (DFNN) consists of multiple *layers*, each in turns has multiple perceptrons. Fig. 8.3 shows a DFNN with input layer, hidden layers, and output layers. The number of perceptrons in each hidden layer can vary. Each layer can be viewed as a function and d number of layers are chained consecutively to form a approximation function $f(x) = f^d(...f^2(f^{(1)}(\mathbf{x})))$. The layers $f^{(1)}, f^{(2)}, ..., f^{(d-1)}$ are called hidden layers and $f^{(d)}$ is called output layer [24]. d is called *depth* of the network. Fig. 8.3 depicts a fully connected deep feedforward network with depth of five layers.

To train DFNN we typically use the *gradient descent* algorithm which aims at finding the parameters $\boldsymbol{\theta} = (\theta_1, \theta_2, ..., \theta_k)$ that minimize the defined loss function. A loss function can be defined as the residual error between model prediction and target value.

$$Loss(\boldsymbol{\theta}) = Error(f(\mathbf{x}; \boldsymbol{\theta}), \mathbf{y}) \tag{8.3}$$

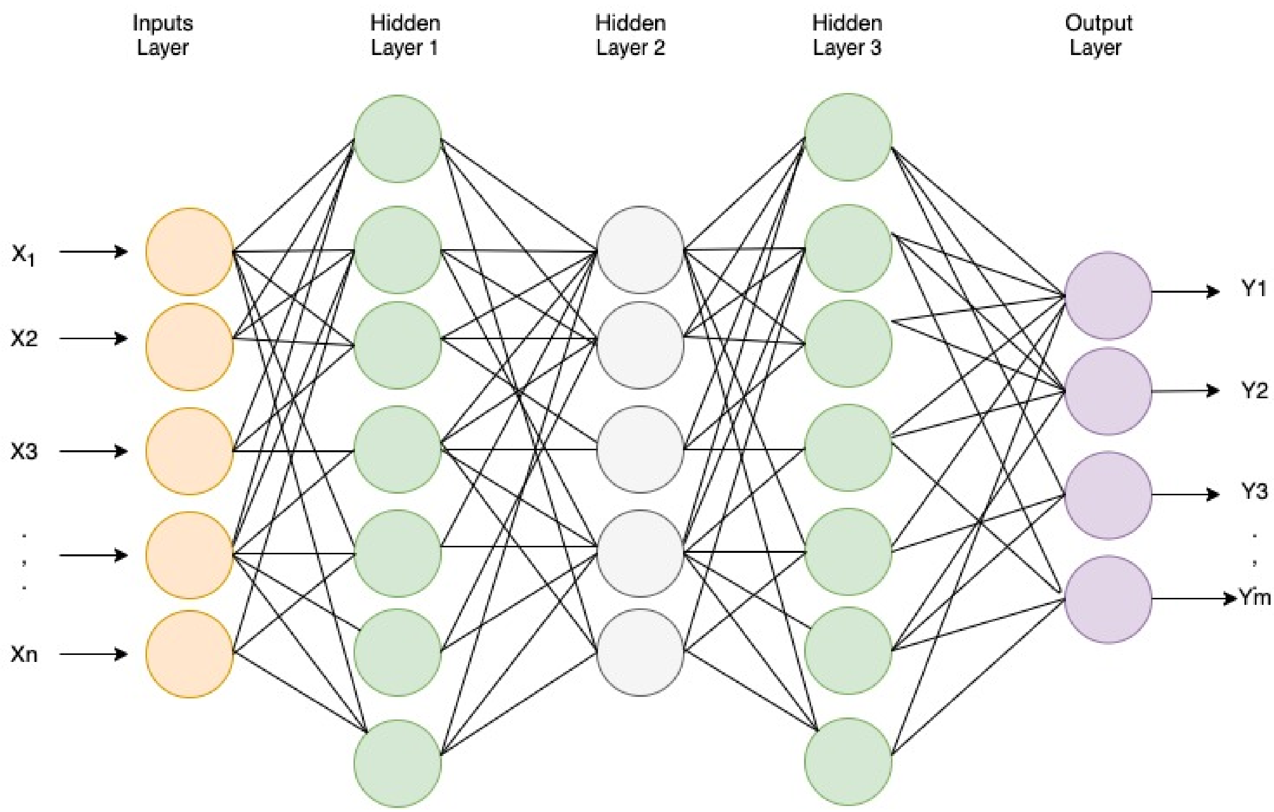


Figure 8.3: A Deep Feedforward Neural Network with five fully connected layers.

The gradient of the loss function can be computed using back-propagation algorithm.

$$\nabla Loss(\boldsymbol{\theta}) = \Big(\frac{\partial Loss}{\partial \theta_1}, ..., \frac{\partial Loss}{\partial \theta_k}\Big) \tag{8.4}$$

Gradient descent method is often used for finding the parameters that minimizes the loss function. This method iteratively updates value of $\boldsymbol{\theta}$ based on a proportion of the loss gradient. The sign of the update value at each iteration is inversely dependent on the direction of the gradient to ensure that the loss always moves towards the local optimum.

$$\boldsymbol{\theta}^{(t)} = \boldsymbol{\theta}^{(t-1)} - \alpha \cdot \nabla Loss(\boldsymbol{\theta}) \tag{8.5}$$

where α is the *learning rate*, which defines how large the value of $\boldsymbol{\theta}$ can be updated at each iteration t. Large value of α can overstep the minimum, whereas too small value makes the algorithm slow to reach the desired optimum.

Convolutional Neural Network

Convolutional Neural Network (CNN) is a type of DFNN that can capture local features from the input. CNN consists of two layers named *convolutional layer* and *pooling layer*. These structure of CNN is shown in Fig. 8.4.

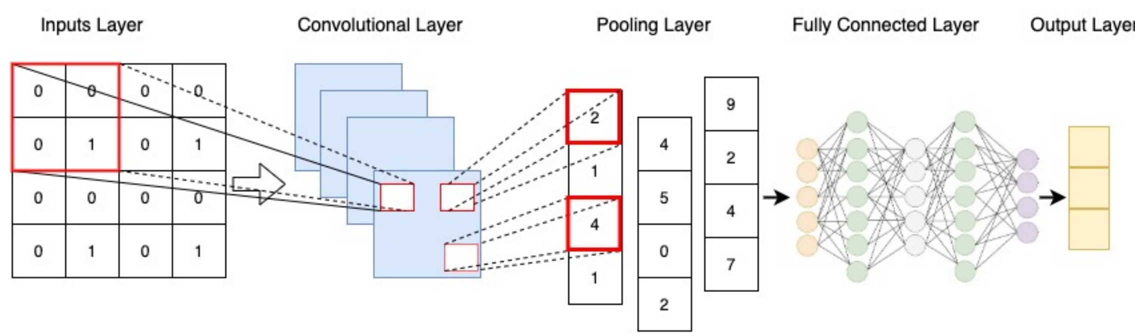


Figure 8.4: Architecture of a general Convolutional Neural Network

Convolutional layer uses transformation matrices (*filter*) to aggregate the input values. It is possible to use multiple filters for convolutional process in which a filter slides through and is replicated on the entire input. The repeated units have shared parameters (weights, bias) and together they form a *feature map*. Fig. 8.5 shows a typical convolutional layer. The main parameters of convolutional layer including

- *Filter size*: the area of region covered by each filter.
- *Number of filters* to apply on the input. Different filters are designed to capture different features from the input.
- *Stride*: the distance between filtered area on the input.

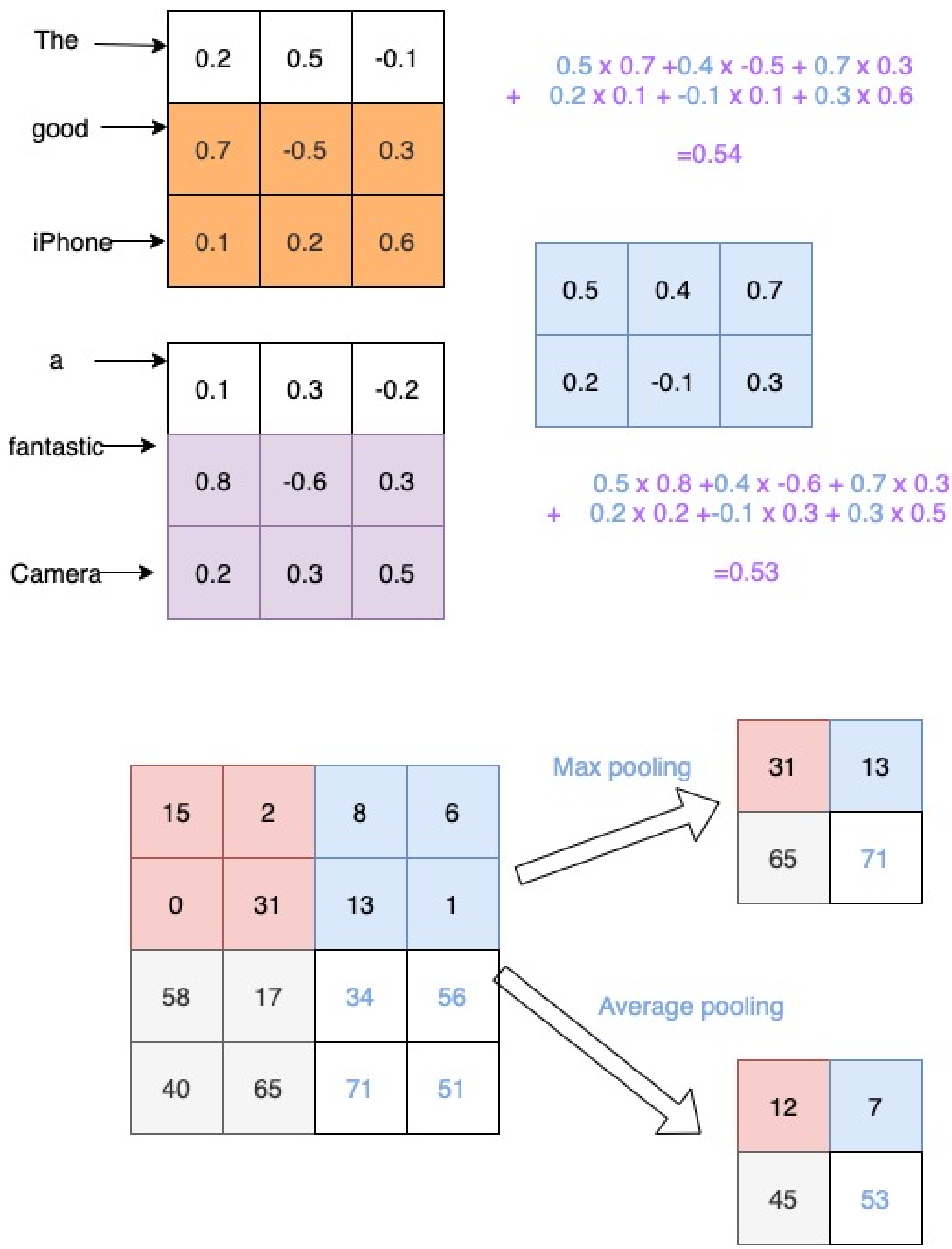


Figure 8.5: Convolution in CNN.

Pooling layer is performed on the output of convolutional layer to downsample the representation of the input. Pooling layer is able to reduce the dimensionality of the features. It allows the subsequent layers to focus on the most relevant signals. Different types of pooling are *max pooling*, *average pooling*, and *dynamic pooling*. Fig. 8.5 presents the two popular pooling techniques.

CNN can be applied for many AI problems in computer vision or image processing problem due to the spatial structure of the input. Regarding to text problem, we can use input transformation techniques to convert them to matrix representation then CNN can be used to achieve very promising results. Another limitation of CNN is the lack of relation between each component in CNN, so a capsule network is proposed for dealing with this limitation.

8.2.2 Capsule Network

A Capsule Neural Network (CapsNet) is a type of neural network model that can be used to better model hierarchical relationships. The Capsule Neural Networks attempts to more closely mimic biological neural organization. CapsNet add "capsules" structures to a Convolutions neural network (CNN). It reuses the output from some of those capsules to form more stable representations (regarding to various perturbations) for higher order capsules. The probability of an observation and a posture for that observation is included in the output vector. This vector is similar to what is done when performing classification with localization in CNNs.

One of the advantage with CapsNet is that of addressing with the "Picasso problem" in image recognition. This problem is referred to the image has all the correct parts but not in the exact spatial relationship (for example, in "faces" ", the position of the mouth and one eye are switched). For image recognition, capsnets exploit the fact that while perspective changes have a nonlinear effect at the pixel level, they have a linear effect at the part / object level. This can be compared to inverting the rendering of an object of multiple parts.

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