Towards visual sentiment summary to understand customers' satisfaction

Dao Thi Thanh Loan[1], Tran Anh Tuan[2,3]
[1]Faculty of Foundational Sciences, Dak Lak College of Pedagogy, Dak Lak, Vietnam
[2]School of Informatics, Walailak University, Nakhon Si Thammarat, Thailand
[3]Informatics Innovation Center of Excellence (IICE), Walailak University, Nakhon Si Thammarat, Thailand

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ABSTRACT

Due to the COVID-19 pandemic, the shopping behavior of customers has been significantly affected and is being shifted towards online shopping. Understanding the customers' opinions, attitudes, and emotions in feedback and comments plays an essential role in making decisions for organizations and individuals (e.g., companies and customers). In this study, we propose sentiment summaries from the customer knowledgebase (SSoCK) framework that analyses customer feedback and improve a mechanism for sentiment summarization by using text analysis including sentiment analysis. In the experiments, various domains from customer reviews (e.g., computer and Canon) are used to conduct. The results show that the proposed SSoCK framework has the high performance of sentiment classification in terms of its accuracy when compared to the other approaches. Moreover, the proposed framework generates various kinds of sentiment summaries that can support managers/potential customers understand trending/interesting aspects of the product with customer satisfaction and can be easily updated with new reviews within the same domain without storing any original data.

Corresponding Author:

Tran Anh Tuan
School of Informatics, Walailak University
Nakhon Si Thammarat, Thailand
Email: tran.tu@wu.ac.th

1. INTRODUCTION

The COVID-19 pandemic has had a significant impact on the shopping behavior of customers. With social distancing measures and restrictions on in-person shopping, many customers have shifted towards online shopping and home delivery services. With internet development, it is easy for customers to share opinions, attitudes, and emotions through social networks (e.g., Facebook and Twister) or provide feedback on websites (e-commercial websites) related to products or services they have purchased or used because of technological advancements. For instance, a customer's feedback on a computer might write "Sound is also nice as compared to its size" [1]. Such comments typically include the user's own words, which are critical in evaluating their level of satisfaction. As a result, these comments and feedback help businesses improve their product or service quality and offer customers valuable insights from others regarding exciting products or services [2]–[10].

The most common way to evaluate customer satisfaction with a product or service is by analyzing their comments and opinions. This provides insight into their sentiments and feelings [11]–[14]. By analyzing these reviews and comments, we can better understand which convey important feedback and which are unim-

portant. This process of tracking customer opinions, emotions, and responses is known as sentiment analysis or opinion mining. Due to the large volume of reviews, organizations and individuals (e.g., companies, governments, internet users, and customers) cannot quickly get major points by reading manually and extracting critical information before making decisions. To overcome this issue, a system is needed to identify and extract essential information and generate valuable summaries. Sentiment summarization based on aspects is one approach that can be applied in this situation (an aspect is a part or an attribute of an object [15]). This sentiment summarization system can generate summaries using aspects by analyzing customer reviews as input and using aspects with polarities to produce a summary output.

Figure 1 is an example of sentences extracted from customers feedback in the *computer* domain [16]. The example has three sentences (S1, S2, and S3) annotated aspects with their polarity. In the sentence S1, there are two aspects: "sound" with "positive" polarity and "size" with "negative" polarity. The polarities ("positive" and "negative") are used to express satisfied level of customers for those aspects. In previous studies, the aspects and their polarities were used to generate sentiment summaries. Hu and Liu [17] proposed a method that uses a bar graph to represent the polarities (positive or negative) of product attributes. Carenini and Rizoli [18] also used a bar chart, but each aspect was depicted separately to show the polarity and opinion strength. Abulaish *et al*. [19] used a bar chart to represent all polarized aspects and the percentage of reviews. Kherwa *et al*. [20] used three different types of charts (bar, Google-o-meter, and pie chart) to visualize aspects with polarities. Kanbur and Aktas [21] depicted the top 10 aspects with polarities from product reviews using a bar chart. Ha *et al*. [22] proposed methods for analyzing sentiment and representing keywords from movie reviews using heatmap visualization, two-dimensional sentiment word map, and asterism graphic. Inácio and Pardo [23] described aspects of electronic products with polarities using a correlation heatmap graph. Tran *et al*. [24] introduced a method for generating visual sentiment summaries based on aspects with polarities from customer reviews using graphs, pie, and word cloud. Hasib *et al*. [25] used bar charts to represent the top 10 words with polarity to analyze the satisfaction levels of Bangladesh airline customers, with each chart illustrating each polarity. Hu *et al*. [26] depicted aspects with polarity using a bubble chart in the domain of student teaching evaluations. Li *et al*. [27] used a column chart to illustrate the number of opinions (positive and negative) for each aspect of customer reviews in the Chinese language. Most studies discussed used visual summaries, such as graphs and charts, to describe different aspects of the data. These aspects were often presented with polarities to help highlight key differences. Despite the popularity of the methods described, there has been a lack of research examining the relationship between customer satisfaction for a whole product across aspects. Meanwhile, the sentiment of each sentence or each comment conveys the satisfaction of one customer for one product or service at the moment the customer expresses their feelings. Therefore, there is a gap needed to do more research.
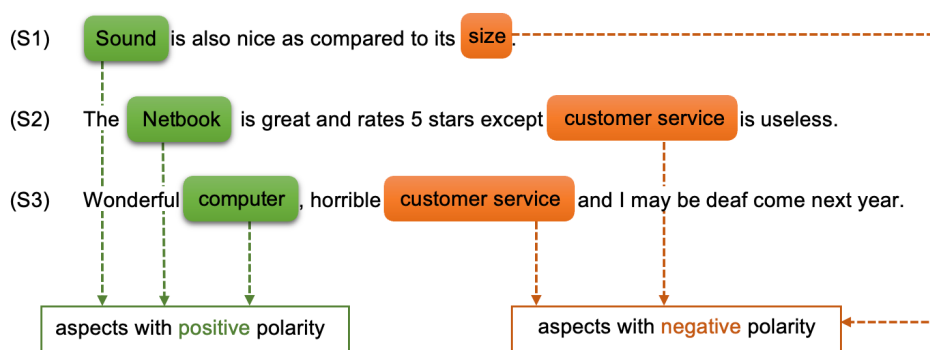

Figure 1. Sentences with aspects and polarity in the computer domain

To have different perspectives of the customer satisfaction by concerning the customer satisfaction on the comments for a whole product including every aspect inside, we propose a framework called sentiment summaries from the customer knowledgebase (SSoCK) in this study to improve a mechanism for sentiment summarization. In the SSoCK framework, text analysis including sentiment analysis is used to determine customer satisfaction with products/services across aspects. Various libraries, including core natural language processing and SentiWordNet, are applied to comments/reviews collected from e-commerce websites to deter-

mine customer satisfaction levels (satisfied, so so, and dissatisfied) on the product/service. Results from the sentiment summaries could support managers or potential customers in making decisions before purchasing products (or using services). The major contributions of this study are as the following: i) introducing the SSoCK framework as a novel approach to generate diverse sentiment summaries that provide insights into trending and exciting aspects of products along with customer satisfaction; ii) offering the framework that can quickly adapt to new reviews within the same domain without storing original data, thereby enhancing scalability and usability; and iii) demonstrating high performance in sentiment classification compared to existing approaches.

2. PROPOSED METHOD

To determine customer satisfaction on aspects of a product or a service through their comments via sentiment summaries, the proposed framework of producing SSoCK is depicted in Figure 2. The SSoCK framework has two main functions: i) customer satisfaction assessment and ii) customer knowledgebase generation. The input of the framework is customer reviews annotated aspects with polarities. The framework output is summaries of the customer knowledgebase based on satisfaction levels and aspects, which are used to support managers/consumers in making decisions.
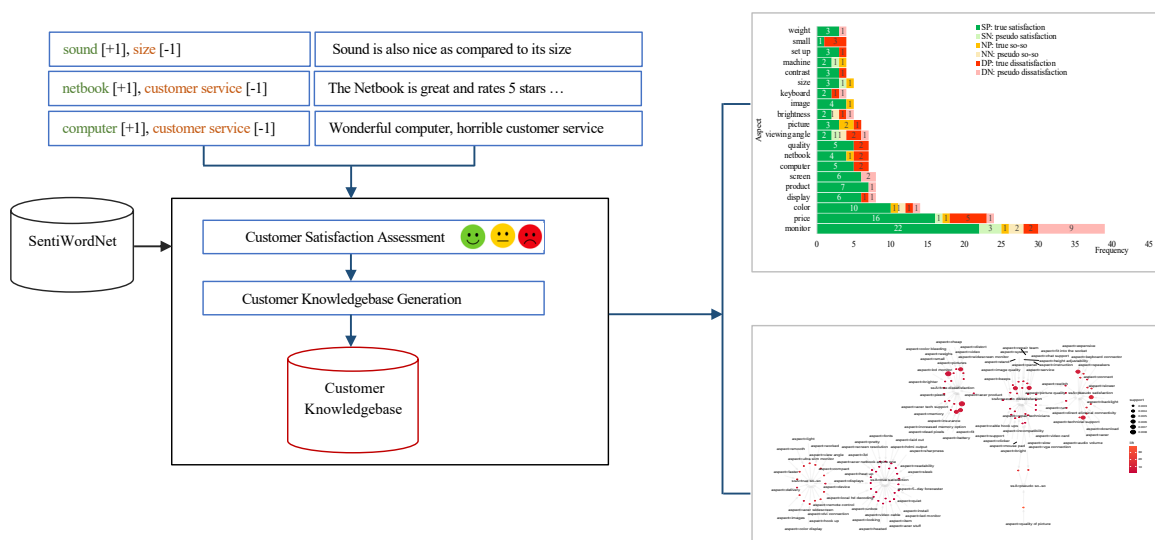

Figure 2. The framework for SSoCK

2.1. Customer satisfaction assessment

The objective of the function is to assess customer satisfaction based on positive and negative scores retrieved from SentiWordNet. SentiWordNet is a lexical resource that assigns sentiment scores to English words based on their meanings [28]. In order to assess customer satisfaction, a sentence is represented by its aspect-polarity-constituents (sAPC) derived from reviews. Before delving into the function in depth, the following definitions are provided:

Let a be a mentioned aspect in sentences, $apList$ be a list of annotated aspects with polarities in one sentence, and pol be the polarity of one aspect in one sentence ($pol \in \{Positive, Negative\}$).

Definition 1 *Positive score (negative score) of one sentence pScore (nScore)* is a total positive score (negative score) of all words in one sentence retrieved from SentiWordNet.

Definition 2 *Customer satisfaction for a sentence (sSent)* is a satisfied level of a customer for a product or a service in the customer's comment and is based on positive and negative scores *(pScore, nScore)* of a sentence as shown in (1).

$$sSent_i = \begin{cases} satisfied & \text{, if } pScore_i > nScore_i \\ so\ so & \text{, if } pScore_i = nScore_i \\ dissatisfied & \text{, if } pScore_i < nScore_i \end{cases} \tag{1}$$

Definition 3 *Sentences based on aspect-polarity-constituents* is a set whose members have a quadruple $< apList, pScore, nScore, sSent >$ in the sentence as shown in (2).

$$\text{sAPC} = \{< apList_i, pScore_i, nScore_i, sSent_i >\} \tag{2}$$

The *sAPC sentences* algorithm in Algorithm 1 is used to represent sentences based on a sAPC. The algorithm initializes the sentences based on sAPC in line 1. In lines 2-12, annotated aspects, polarities, and constituents in each sentence of the review are extracted. For each sentence, all members of the sAPC are initialized, and the sentence is split into two parts. The former, saved in tAP, includes the annotated aspects and polarities, while the latter, dedicated in tS, consists of the rest of the content. For each aspect in the tAP, its polarity is checked. If the polarity of an aspect a_j equals +1/+2/+3, its pol_j is assigned "positive". Conversely, if the polarity of an aspect a_j equals -1/-2/-3, its pol_j is assigned "negative". The aspect a_j and pol_j are added to $apList_i$. For each word in the tS, positive and negative scores of the word j are retrieved from SentiWordNet. The positive and negative scores of the sentence are added to the respective positive and negative scores of the word j retrieved from SentiWordNet. After that, the $(apList_i, pScore_i, nScore_i)$ is added into the sAPC. On line 13, the algorithm returns the sAPC after processing all the sentences in the review.

Algorithm 1: sAPC Sentences

Input : Review R, SentiWordNet
Output : sAPC = $\{< apList_i, pScore_i, nScore_i, sSent_i >\}$

1 **for** *each sentence i in* R **do**
2 $\quad apList_i \leftarrow \emptyset$ /* $apList_i$ saves aspects and polarities from the sentence i^{th}*/
3 $\quad pScore_i, nScore_i \leftarrow 0$
4 $\quad tAP \leftarrow$ extract annotated aspects and polarities in the sentence i^{th}
5 $\quad tS \leftarrow$ extract a content of sentence i^{th} without annotated aspects and polarities
6 $\quad$ **for** *each aspect a_j in tAP* **do**
7 $\quad\quad$ add (a_j, "positive") to $apList_i$ if polarity of a_j is in { +1 , +2, +3 }
8 $\quad\quad$ add (a_j, "negative") to $apList_i$ if polarity of a_j is in { -1 , -2, -3 }
9 $\quad$ **for** *each word w_j in tS* **do**
10 $\quad\quad$ calculate $pScore_i$ and $nScore_i$
11 $\quad$ calculate $sSent_i$ with a formula (1)
12 $\quad$ add ($apList_i, pScore_i, nScore_i, sSent_i$) to sAPC
13 **return** the sentence based sAPC

For example, the following sentences annotated aspect(s) and polarity in the *Computer* domain are used to illustrate examples of calculation methods for concepts: *C1) "monitor[-1] ## My overall experience with this monitor was very poor."; C2) "monitor[-1], picture quality[-1] ## I've viewed numerous different monitor models since I'm a college student and this particular monitor had as poor of picture quality as any I've seen."; C3) "sound[+1], size[-1] ## Sound is also nice as compared to its size."; C4) "netbook[+1], customer service[-1] ## The Netbook is great and rates 5 stars except customer service is useless."; C5) "computer[+1], customer service[-1] ## Wonderful computer, horrible customer service, and I may be deaf come next year"*. The sentence C1 ($i = 1$) is calculated using (1) and Algorithm 1. In this case, "monitor [-1]" is the annotated aspect with a negative polarity in sentence C1, represented as $apList_1 = \{(monitor, "negative")\}$. The text in sentence C1, "My overall experience with this monitor was very poor", is used to calculate the other scores by employing SentiWordNet and (1). The scores are as follows: $pScore_1 = 0.63$, $nScore_1 = 1.25$, and $sSent_1 =$ "dissatisfied". Consequently, the first quadruple of sAPC is $\{< \{(monitor, "negative")\}, 0.63, 1.25, "dissatisfied" >\}$. The completed sAPC for the five sentences is presented in Table 1.

Table 1. An example of sAPC for sentences C1 to C5

i	$apList_i$	$pScore_i$	$nScore_i$	$sSent_i$
1	{("monitor", "negative")}	0.63	1.25	"dissatisfied"
2	{("monitor", "negative"), ("picture quality", "negative")}	1.50	1.00	"satisfied"
3	{("sound", "positive"), (size, "negative")}	1.25	0.63	"satisfied"
4	{("netbook", "positive"), (customer service, "negative")}	0.63	0.88	"dissatisfied"
5	{("computer", "positive"), ("customer service", "negative")}	1.00	0.75	"satisfied"

2.2. Customer knowledgebase generation

The function aim is to generate customer knowledgebase from the customer reviews processed in the previous step. The customer knowledgebase used to produce summaries consists of two parts that: i) *satisfaction and aspect knowledgebase based on frequencies* (saF) and ii) *satisfaction and aspect knowledgebase based on rules* (saR). Before exploring the procedure in detail, the subsequent definitions are presented:

Definition 4 *Customer satisfaction for an aspect in a sentence (ssA)* is a satisfied level of a customer for an aspect of a product or a service in the customer's comment and is aggregated from the polarity of the aspect *(pol)* and customer satisfaction for a sentence *(sSent)* as shown in (3).

$$ssA_{il} = \begin{cases} true\ satisfaction & , \text{if } sSent_i = satisfied \bigwedge pol_{a_{il}} = positive \\ pseudo\ satisfaction & , \text{if } sSent_i = satisfied \bigwedge pol_{a_{il}} = negative \\ true\ so-so & , \text{if } sSent_i = so\ so \bigwedge pol_{a_{il}} = positive \\ pseudo\ so-so & , \text{if } sSent_i = so\ so \bigwedge pol_{a_{il}} = negative \\ true\ dissatisfaction & , \text{if } sSent_i = dissatisfied \bigwedge pol_{a_{il}} = positive \\ pseudo\ dissatisfaction & , \text{if } sSent_i = dissatisfied \bigwedge pol_{a_{il}} = negative \end{cases} \quad (3)$$

where l is the aspect l^{th} in a sentence.

Let sp, sn, np, nn, dp, and dn be frequencies of an respective aspect "true satisfaction", "pseudo satisfaction", "true so-so", "pseudo so-so", "true dissatisfaction", and "pseudo dissatisfaction".

Definition 5 *satisfaction and aspect knowledgebase based on frequencies* (saF) is a set whose members have a septuple $< a, sp, sn, np, nn, dp, dn >$ as shown in (4).

$$\text{saF} = \{< a_k, sp_k, sn_k, np_k, nn_k, dp_k, dn_k >\} \quad (4)$$

where k is an index of a non-redundant aspect ($1 \leq k \leq$ m), m is the total number of non-redundant aspects.

Definition 6 *satisfaction and aspect knowledgebase based on rules* (saR) is a set of rules whose members have a quintuple $< lhs, lhr, supp, conf, lift >$ as shown in (5).

$$\text{saR} = \{< lhs_q, lhr_q, supp_q, conf_q, lift_q >\} \quad (5)$$

where q is a rule q^{th} ($1 \leq q \leq$ r), r is the total number of rules, lhs, lhr are left hand side and right hand side in the rule, $supp, conf, lift$ are support, confident, and lift ratios for the rule.

For example, the items in a septuple $< a_1, sp_1, sn_1, np_1, nn_1, dp_1, dn_1 >$ for the aspect "monitor" ($k = 1$) are calculated as follows: from sentence C1 ($i = 1$) in Table 1, $sSent_1$ is "dissatisfied", the aspect "monitor" carries a negative polarity ($pol_{a_{11}} = negative$), it means ssA_{11} = "pseudo dissatisfaction", the value of dn for $k = 1$ increases by one. Consequently, after calculating the first sentence in sAPC for the five sentences (C1 to C5), the first septuple of saF becomes {<monitor, 0, 0, 0, 0, 0, 1>}. By applying the same procedure to all sentences in sAPC, the completed saF for the sAPC of the five sentences is presented in Table 2. Note that the top r rules generated by the Apriori algorithm select and save saR.

Table 2. An example of saF for sAPC of sentences C1 to C5

k	a_k	sp_k	sn_k	np_k	nn_k	dp_k	dn_k
1	"monitor"	0	1	0	0	0	1
2	"picture quality"	0	1	0	0	0	0
3	"sound"	1	0	0	0	0	0
4	"size"	0	1	0	0	0	0
5	"netbook"	0	0	0	0	1	0
6	"customer service"	0	1	0	0	0	1
7	"computer"	1	0	0	0	0	0

3.   RESULT AND DISCUSSION

In this study, customer reviews in multiple domains (Computer, Canon G3, Canon SD500, Canon S100, Linksys router, Hitachi router, Norton, Nokia 6610, and Diaper Champ) [1], [16], [29] are used to conduct our experiments. Each domain is depicted with the format domain_name [total of sentences; number of negative aspects; number of positive aspects] as the following: Computer [531; 84; 270], Canon G3 [597; 61; 225], Canon SD500 [229; 27; 121], Canon S100 [298; 55; 163], Linksys router [577; 63; 155], Hitachi router [312; 79; 186], Norton [380; 167; 70], Nokia 6610 [546; 86; 253], and Diaper Champ [375; 56; 183]. Multi-layer perceptron (MLP) and support vector machine (SVM), and three methods of feature selection, bag of word (BoW), term frequency-inverse document frequency (TF-IDF), and proposed method based on SentiWordNet (SWN-based), are used to conduct experiments to validate results in the phase of sentiment classification, in which the MLP and SVM techniques had high performance in sentiment classification tasks [2]. Some hyper-parameters in these machine learning techniques are adjusted and adapted to obtain the best result. For the SVM technique, a kernel function is *linear*. For the MLP technique, the active function is *Relu*. The number of hidden neurons is determined using the formula $h = (2c^2 + 1)/(3c + 1)$, where c is the number of inputs [30]. In this part, we compare a phase of sentiment classification in the proposed framework with other approaches by using the accuracy metric. The formula for the accuracy metric is [29]: $Accuracy = (TP + TN)/(TP + TN + FP + FN)$. Each domain is divided into two parts, one for training and the other for testing, with a ratio of seven to three. The accuracy of the machine learning techniques is presented in Table 3, which includes the classifiers and feature selection methods in the first two columns, and the accuracy results for domains R1-R9 in the remaining columns. The SWN-based feature selection method outperformed BoW and TF-IDF methods, achieving higher accuracy in domains R1, R3, R5, R6, R7, and R9 for both the MLP and SVM techniques. In domains R4 and R8, the SVM technique with the SWM-based method exhibited superior performance. Additionally, in domain R2, the MLP technique with the SWM-based method showed better accuracy compared to other approaches (Figure 3 and Table 3).

Table 3. Accuracy results of machine learning techniques for R1-R9 domains

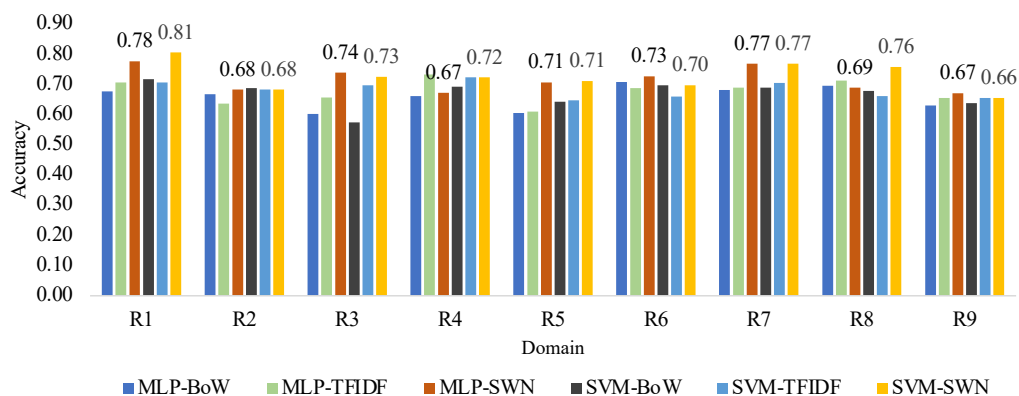| Classifier	Feature selection	R1	R2	R3	R4	R5	R6	R7	R8	R9
MLP	BoW	0.68	0.67	0.60	0.66	0.61	0.71	0.68	0.70	0.63
	TF-IDF	0.71	0.64	0.66	0.73	0.61	0.69	0.69	0.71	0.66
	SWN-based	**0.78**	**0.68**	**0.74**	0.67	**0.71**	**0.73**	**0.77**	0.69	**0.67**
SVM	BoW	0.72	0.69	0.58	0.69	0.64	0.70	0.69	0.68	0.64
	TF-IDF	0.71	0.68	0.70	0.72	0.65	0.66	0.71	0.66	0.66
	SWN-based	**0.81**	0.68	**0.73**	**0.72**	**0.71**	**0.70**	**0.77**	**0.76**	**0.66**

Figure 3. Comparison of accuracy for sentiment classification of R1-R9 domains

The customer knowledgebase generated by the previous phases is used to produce visual sentiment summaries to let the managers/potential customers quickly observe the products. In this result, the customer knowledgebase of the *computer* domain is used to generate visual sentiment summaries. Figures 4 and 5 show visual sentiment summaries based on the customer knowledgebase. Figure 4 showcases the frequencies of

these aspects across different satisfaction levels. The most exciting aspect discussed by customers was "monitor", which appeared 39 times in total, including 22 instances of true satisfaction, three instances of pseudo satisfaction, one instance of true so-so, two instances of pseudo so-so, two instances of true dissatisfaction, and nine instances of pseudo dissatisfaction. Figure 5 presents a summary of the top 100 rules derived from the customer knowledgebase in the computer domain. This summary supports the rapid identification of patterns related to aspects and customer satisfaction. Among the six levels of customer satisfaction, the "pseudo dissatisfaction" level exhibits the highest number of rules, with 25 rules, followed by "true satisfaction" with 23 rules, "true dissatisfaction" with 18 rules, "pseudo satisfaction" with 16 rules, "true so-so" with 15 rules, and "pseudo so-so" with only three rules. Moreover, from the summary we can determine that aspects within the two clusters of customer satisfaction (true satisfaction and true so-so) were segregated independently. However, some aspects were present in multiple clusters. For instance, the aspect "picture quality" was assessed in both the pseudo-satisfaction and pseudo-dissatisfaction clusters.
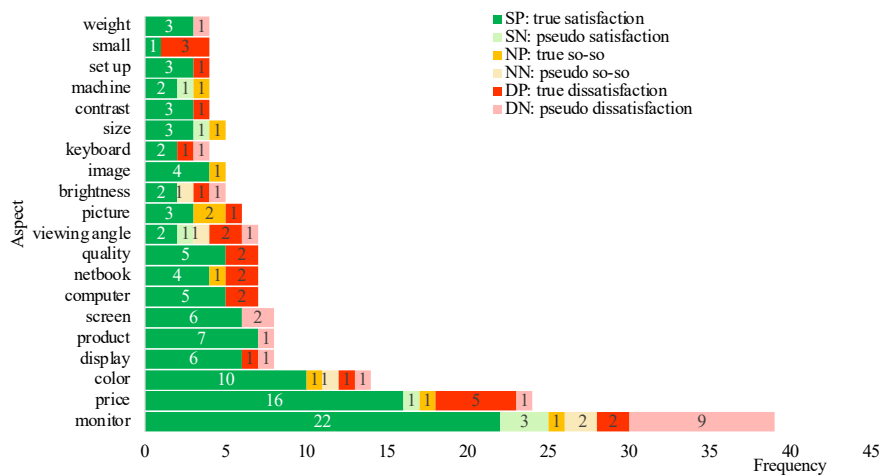

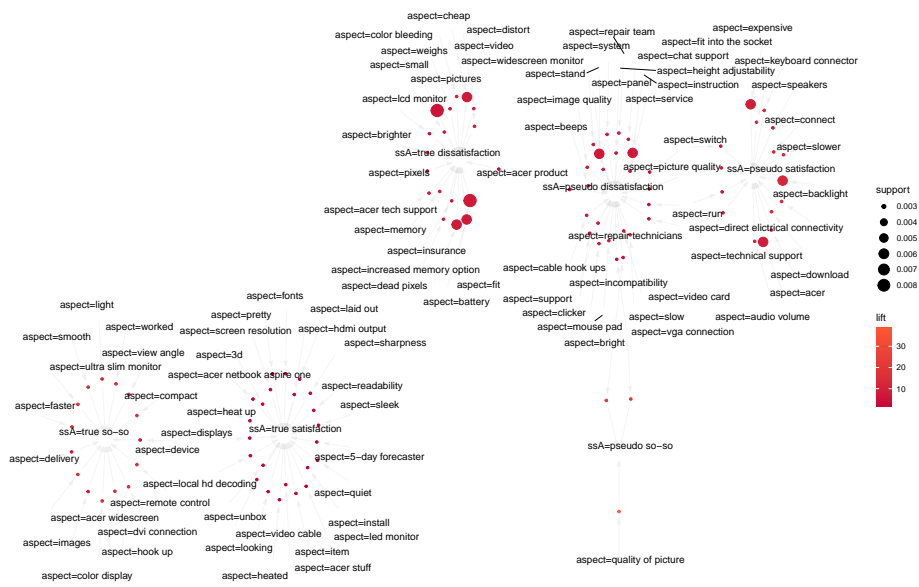Figure 4. Aspects with frequencies cross satisfaction levels for the computer domain

Figure 5. The visual sentiment summary based on top rules for the computer domain

Figure 6 showcases visual sentiment summaries for the *Canon* domain, in which Figure 6(a) represents each aspect with polarities (positive and negative) in a bar chart [29], Figure 6(b) depicts aspects ("picture" and "battery") with polarities ("hate very much, "hate", "dislike", "neither like nor dislike", "like", "love", "love very much") in a pie chart [24], and Figure 6(c) describes each aspect with six levels of customer satisfaction ("true satisfaction", "pseudo satisfaction", "true so-so", "pseudo so-so", "true dissatisfaction", and "pseudo dissatisfaction"). By comparing our framework with existing systems, our findings indicate the superiority of our approach in terms of clarity, comprehensiveness, and ease of use.
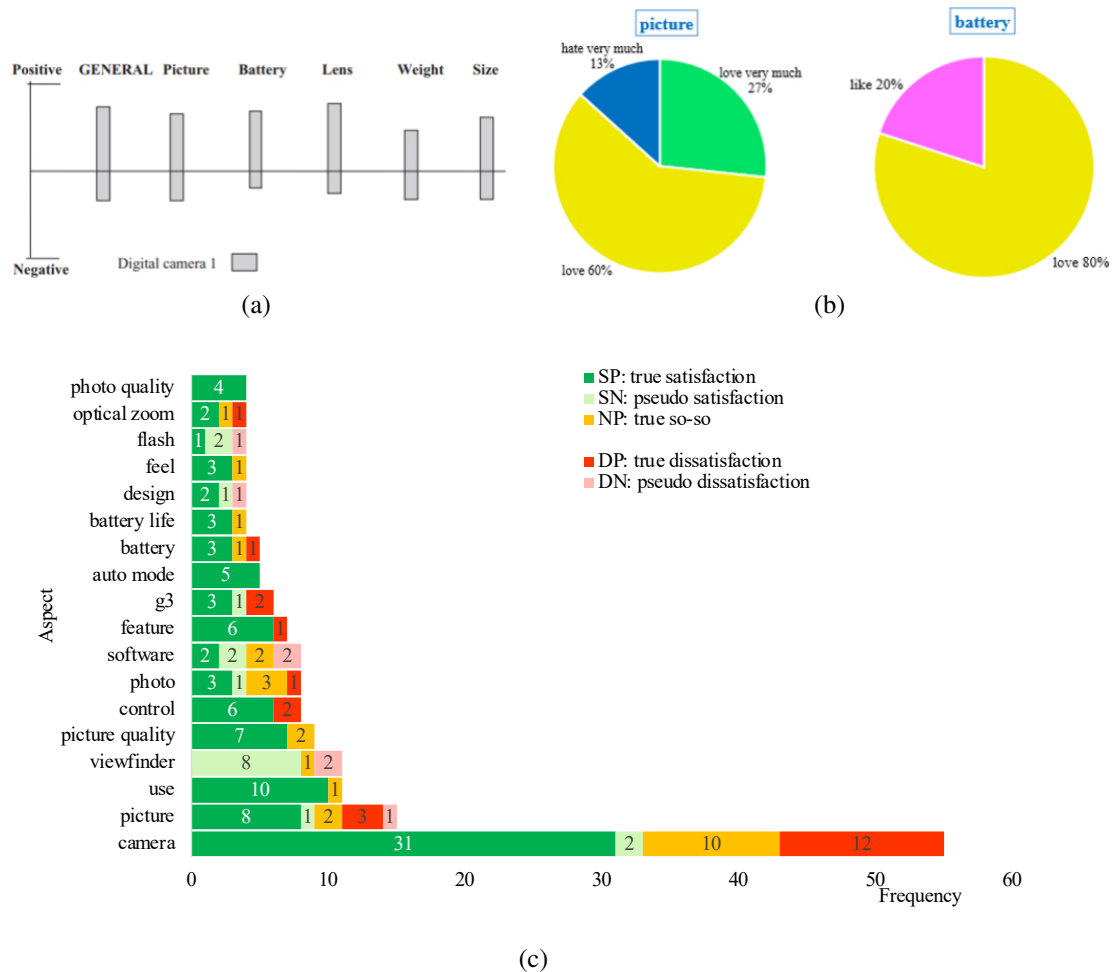

(a)

(b)

(c)

Figure 6. A comparison of the visual sentiment summaries for the Canon domain; (a) the visual summary for aspects and polarities in a bar chart [29], (b) the visual summary for the aspects and polarities in a pie chart [24], and (c) the visual summary produced by the proposed SSoCK

4. CONCLUSION

This study aimed to introduce a framework for generating visual sentiment summaries from customers' feedback or comments regarding customer satisfaction with a whole product/service, encompassing all aspects. The framework, called SSoCK, utilized text and sentiment analysis to assess customer satisfaction across various product/service aspects. By leveraging the customer knowledgebase, the framework generated sentiment summaries highlighting trending aspects with customer satisfaction, aiding prospective consumers in decision-making. These summaries can be updated easily with new reviews within the same domain without storing original data. The results of the framework's performance on customer review domains had high accuracy for sentiment classification compared to other approaches. The findings from the sentiment summaries

could support managers or potential customers in making decisions that are based on trending/exciting aspects of customer satisfaction.

Despite its advantages, the SSoCK framework has certain limitations. It requires annotated input with aspects and polarity, rendering it unsuitable for real-time search applications. However, the authors plan to address these limitations in future framework iterations. Specifically, we intend to develop a component that can apply the SSoCK framework to datasets without annotations. Additionally, we aim to incorporate options within the framework for selecting data sources provided by users or retrieved from the internet, further enhancing its versatility and applicability.

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BIOGRAPHIES OF AUTHORS

Dao Thi Thanh Loan (ID) (icons) is a lecturer at Faculty of Foundational Sciences, Dak Lak College of Pedagogy, Vietnam. She got her B.Eng. and M.Sc. in Computer Science from Posts and Telecommunications Institute of Technology, HCMC campus and Hanoi National University of Education, Vietnam. Her research interests are soft computing, database, and machine learning. She can be contacted at email: loanthithanhdao@gmail.com.

Tran Anh Tuan (ID) (icons) is a lecturer at School of Informatics, Walailak University, Thailand. He got his B.Sc. in Information Technology from Hue University of Education, M.Sc. in Information System from HCMC University of Sciences, Vietnam, and Ph.D. in Computer Science from Prince of Songkla University, Thailand. His research interests are natural language processing, machine learning, and data science. He can be contacted at email: tran.tu@wu.ac.th.