

# A new approach for extracting and scoring aspect using SentiWordNet

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## ABSTRACT

Aspect-based online information on social media plays a vital role in influencing people's opinions when consumers concern with their decisions to make a purchase, or companies intend to pursue opinions on their product or services. Determining aspect-based opinions from the online information is necessary for business intelligence to support users in reaching their objectives. In this study, we propose the new aspect extraction and scoring system which has three procedures. The first procedure is normalizing and tagging part-of-speech for sentences of datasets. The second procedure is extracting aspects with pattern rules. The third procedure is assigning scores for aspects with SentiWordNet. In the experiments, benchmark datasets of customer reviews are used for evaluation. The performance evaluation of our proposed system shows that our proposed system has high accuracy when compared to other systems.

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## 1. INTRODUCTION

Nowadays, the digital era affects humans' behaviors in choosing reference resources to decide their decisions. The online information usually composes of opinions or feelings expressed by the Internet users about services, healthcare, products, politics, etc. Determining and understanding the Internet users' opinions (e.g., happy or unhappy) using sentiment analysis is the vital key-role to apply to marketing, and making decisions or recommendations [1–3].

In textual online information, the users usually mention about opinions or feelings. These attributes are called aspects, and the phase to extract the useful aspects from the online information is called aspect extraction [4–8]. In the previous works, most of these studies extracted aspects from customers' reviews and did not show how much satisfied or dissatisfied the Internet users mentioned in reviews for the aspects. To determine and understand how much satisfied or dissatisfied the Internet users mention for aspects is useful to make decisions. In this study, we propose aspect extraction and scoring system (AESS) to extract and score aspects which become the knowledgebase. Datasets from independent domains (e.g., services, products, etc.) are the input of the AESS. The pre-processing phase is normalizing and tagging part-of-speech (POS). The AESS uses pattern rules to extract aspects from datasets. SentiWordNet is used to assign score levels for aspects. The output is the scored aspect knowledgebase which shows satisfied levels of the users as well.

The rest of the paper is organized as the following: The related works are presented in section 2. The

architecture of the proposed AESS system is discussed in section 3. The experimental results and evaluation are explained in section 4. Finally, the conclusion is given in section 5.

## 2. RELATED WORK

To extract aspect, Wei *et al.* [9] proposed semantic-based product feature extraction (SPE) method which used the association rule mining algorithm to extract aspects. Qiu *et al.* [10] presented a double-propagation (DP) algorithm which used dependency relations among constituencies in a sentence to extract aspects. Liu *et al.* [4] extended more dependency relations (DP<sup>+</sup>) to extract aspects. Rana and Cheah [11] proposed a two-fold rules-based model (TF-RBM) which used sequential pattern rules to extract aspects. Mataoui *et al.* [12] introduced a method for the Arabic language by using syntactic rules in order to extract aspects. Rana and Cheah [13] proposed a sequential pattern rules-based approach (SPR) to automatically produce sequential pattern rules to extract aspects. Poria *et al.* [14] suggested rules and dependency trees to extract aspects (explicit and implicit). Meanwhile, Alqaryouti *et al.* [15] used rules to extract aspects (explicit and implicit) from government reviews.

For aspect scoring, Kherwa *et al.* [16] assigned a score for an aspect by calculating an average score of opinion words from SentiWordNet where these opinion words and that aspect co-occurred. Asghar *et al.* [17] chose the highest score in three scores (positive, negative, objective) of an opinion word which were respective average scores of all synsets of that opinion word from SentiWordNet. Xu *et al.* [18] used frequency and a dictionary to calculate scores. Jmal and Faiz [19] calculated a score by using the popularity of a frequency for one aspect on Twitter and scores (negative, positive, neutral) from SentiWordNet of words (verb/adjective) related to the aspect. The frequency of the aspect was estimated in the dataset. Meanwhile, Maheswari and Dhenakaran [20] used a dictionary for opinion words and Fuzzy rules.

## 3. PROPOSED METHODOLOGY

To automatically extract and score aspects from datasets, the AESS is proposed and illustrated in Figure 1. The AESS system has three procedures: 1) pre-processing, 2) aspect extraction using pattern rules and Word2Vec, and 3) aspect scoring using SentiWordNet. The input of the system is datasets such as product reviews. The output of the system is the scored aspect knowledgebase which can be represented in graphics.

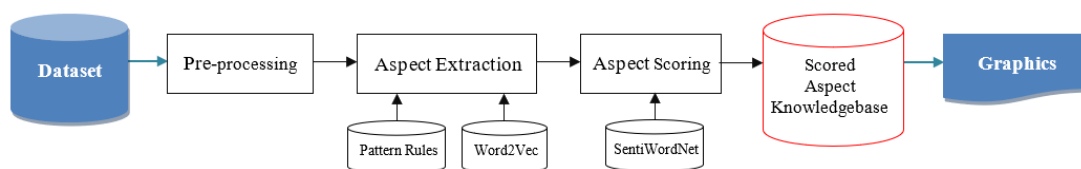


Figure 1. An architecture of AESS

### 3.1. Pre-processing

This procedure aims to normalize and tag POS for sentences of datasets. The details are 1) eliminating special characters in the text of social media, e.g., HyperText markup language (HTML) tags, a pair of quotations, 2) correcting misspelt words, and 3) tagging POS for text.

### 3.2. Aspect extraction

This procedure is used to extract aspects with opinion words and intensifier words from datasets using pattern rules. There are two main steps: 1) aspect candidates extraction, and 2) aspect pruning.

Let  $a$  be an aspect,  $ow$  be an opinion word in the (opinion lexicons) OL, and  $iw$  be an intensifier word. Let  $neg$  be a negation status which shows a negation word existing in a sentence with an opinion word where  $neg \in \{True, False\}$ .

Definition 1: Sentence based on aspect-opinion-intensifier (SAOI) is a set which members have a quadruple  $\langle a, ow, iw, neg \rangle$  in the sentence as shown in (1)

$$SAOI = \langle a_i, ow_i, iw_i, neg_i \rangle \quad (1)$$

where  $i$  is an index of an extracted aspect,  $1 \leq i \leq n$ ,  $n$  is the number of extracted aspects.

- Step 1. aspect candidates extraction. This step will extract aspect candidates from datasets by using the pattern rules and the OL dictionary (Bing Liu's opinion lexicon [21] and MPQA's opinion lexicon [22]). After extracting, the aspects, opinion words, and intensifier words are saved in SAOI. The pattern rules are determined by using the relationship between aspect and opinion words. The relationships based on a syntactic structure are determined from the dependency tree [23]. Some examples of the pattern rules are in Table 1. There are opinion word(s) in italic, aspect(s) in bold, co-reference word(s) in italic bold, optional words in brackets, and a subscript showing positions for a constituent in a sentence (e.g., "a", "b", etc.).
- Step 2. aspect pruning. This step eliminates the irrelevant aspects by using the cosine similarity and Word2Vec (Word2Vec is provided by SpaCy [24]).

Table 1. Some examples of pattern rules for aspect extraction

Pattern No.	Syntax-based Pattern Rule	Pattern No.	Syntax-based Pattern Rule
S1	<i>AP</i> + <b>CN</b>	S6	<b>CN</b> + RCI + V2A + <i>AP</i> (Note: RCI is any pattern)
S2	<b>CN</b> + <i>RCI</i>	S7	<b>CN<sub>a</sub></b> + V + (Prep) + <b>CN<sub>b</sub></b> + V2A + <i>AP</i> Note: Prep is "by"; V is V+ed / V+ing
S3	V2A + (Adv) + A2 + <b>NP</b>	S8	Pron <sub>1</sub> + V/V2A + <b>CN</b> + (Adv) + Conj + <b>Pron<sub>2</sub></b> + V2A + <i>AP</i> Note: Pron <sub>2</sub> is a co-reference of CN
S4	<b>CN</b> + V2A + <i>AP</i>	S9	(Adv) + V2 + <b>NP</b>
S5	<b>CN<sub>a</sub></b> + V2A + <b>CN<sub>b</sub></b>	S10	<b>CN</b> + V2A + V (Note: V is V+ed / V+ing)

### 3.3. Aspect scoring

A goal of this procedure is to score aspects by using SentiWordNet (SentiWordNet which is a lexical resource is automatically annotated "positivity" and "negativity" scores for all of synsets [25]).

Definition 2: Opinion value of an opinion word (*OV*) is an average of all synsets values for an opinion word (*ow*) which are retrieved from SentiWordNet as shown in (2)

$$OV = \begin{cases} (\sum_{i=1}^p PV_i) / p & , \text{ if } ow \in \text{OLP} \\ (\sum_{i=1}^p NV_i) / p & , \text{ if } ow \in \text{OLN} \end{cases} \quad (2)$$

where *p* is a number of entries (synsets) for *ow* in SentiWordNet,  $PV_i$  is the  $i^{th}$  positive value,  $NV_i$  is the  $i^{th}$  negative value, OLP is a set of Opinion Lexicons in Positive (e.g., "good", "great", etc.), and OLN is a set of Opinion Lexicons in Negative (e.g., "bad", "hate", etc.) ( $OL = \text{OLP} \cup \text{OLN}$ ).

Definition 3: Sentence polarity (*SPol*) is a value which is aggregated from a negation status *neg* and an opinion word (*ow*) in a sentence as shown in (3)

$$SPol = \begin{cases} +1 & , \text{ if } polarity_{ow} \oplus neg = True \\ -1 & , \text{ if } polarity_{ow} \oplus neg = False \end{cases} \quad (3)$$

where *neg* is a negation word exists in a sentence or not, and  $polarity_{ow}$  is a polarity of an opinion word ( $polarity_{ow}$  is equal to *True* if an opinion word (*ow*) is positive.  $polarity_{ow}$  is equal to *False* if an opinion word (*ow*) is negative).

For example, from the sentence "A picture is not beautiful", an opinion word "beautiful" is positive. Polarity of "beautiful" is determined True. A negation word is "not". *neg* for "not" is True. With  $polarity_{ow} = True$  and  $neg = True$ ,  $polarity_{ow} \oplus neg$  and *SPol* equal to False and -1, respectively. Let  $IV_{iw}$  be an Intensifier Value of an intensifier word (*iw*).  $IV_{iw}$  is pre-defined by users in Table 2 and has the value in [-1, 1].

Definition 4: SAOI score for an aspect ( $SScore_a$ ) is a value which is aggregated from values of an opinion word, an intensifier word, and negation expressed by users' opinions for aspect *a* in one sentence as shown in (4).

$$SScore_a = SPol \times \left[ (IV_{iw} \times OV) + OV \right] \quad (4)$$

For example, SAOI Score for an aspect  $SScore_a$  for a quadruple ("speed", "good", "so", *False*) in Table 3 ( $i = 1$ ) from the sentence "The speed is so good" is calculated with Formula (4) as follows: "good" is positive opinion (i.e.  $polarity_{ow} = True$ ).  $SPol = +1$  because  $neg = False$  and  $polarity_{ow} = True$ .

Intensifier word “so” has intensifier value 0.45 (i.e.  $IV_{iw} = 0.45$ ).  $OV$  for “good” is an average score which is retrieved from SentiWordNet and is equal to 0.70. Hence,  $SScore_a = (+1) \times [(0.45 \times 0.70) + 0.70] = 1.02$ . The example of  $SScore_a$  for aspects are shown in Table 3.

Table 2. Intensifier values ( $IV_{iw}$ ) for intensifier words ( $iw$ )

Intensifier word(s) ( $iw$ )	Intensifier Value ( $IV_{iw}$ )	Intensifier word(s) ( $iw$ )	Intensifier Value ( $IV_{iw}$ )
awfully, critically	-1.00	altogether, so	0.45
dangerously, dreadfully, hopelessly	-0.70	primarily, very	0.50
bitterly, horribly, strikingly	-0.50	highly	0.55
terribly, violently	-0.50	largely, reasonably	0.60
suspiciously, slightly	-0.40	greatly	0.65
somewhat	-0.25	hugely, surprisingly, totally, utterly	0.70
mildly, quite	-0.20	fully, mainly, deeply	0.70
faintly	0.10	especially, particularly, predominantly	0.75
really, purely	0.15	amazingly, exceedingly, extremely	0.80
remarkably, nearly, partly	0.20	incredibly, seriously, unbelievably	0.80
pretty, rather, roughly	0.20	wonderfully, exclusively	0.80
simply	0.25	entirely, almost, mostly	0.90
fairly, moderately	0.30	absolutely, completely, perfectly	1.00

Table 3. Examples of  $SScore_a$  and score level for aspects

$i$	SAOI				$SPol$	$IV_{iw}$	$OV$	$SScore_a$	score level	
	$a_i$	$ow_i$	$iw_i$	$neg_i$					number	name
1	speed	good	so	False	+1	0.45	0.70	1.02	+2	very satisfied
2	battery	good	“”	True	-1	0	0.70	-0.70	-2	very dissatisfied
3	battery	loved	“”	False	+1	0	0.71	0.71	+2	very satisfied
4	speed	bad	“”	True	+1	0	0.66	0.66	+1	satisfied
5	battery	cool	quite	False	+1	-0.20	0.29	0.23	+1	satisfied
6	battery	good	“”	False	+1	0	0.70	0.70	+2	very satisfied
7	speed	bad	“”	False	-1	0	0.66	0.66	+1	satisfied

Definition 5: Score level is a pair of two data (number, name) in which “number” is an integer number in  $[-3, +3]$ , and “name” is (“the most dissatisfied”, “very dissatisfied”, “dissatisfied”, “so so”, “satisfied”, “very satisfied”, “the most satisfied”). Relations between number and name are  $\{(-3, \text{“the most dissatisfied”}), (-2, \text{“very dissatisfied”}), (-1, \text{“dissatisfied”}), (0, \text{“so so”}), (+1, \text{“satisfied”}), (+2, \text{“very satisfied”}), (+3, \text{“the most satisfied”})\}$ .

Score level for an aspect  $a$  ( $SL_a$ ) is determined by using  $SScore_a$  as shown in (5)

$$SL_a = \begin{cases} (-3, \text{“the most dissatisfied”}) & , \text{ if } SScore_a \leq -1.4 \\ (-2, \text{“very dissatisfied”}) & , \text{ if } SScore_a \in (-1.4, -0.7] \\ (-1, \text{“dissatisfied”}) & , \text{ if } SScore_a \in (-0.7, 0) \\ (0, \text{“so so”}) & , \text{ if } SScore_a = 0 \\ (+1, \text{“satisfied”}) & , \text{ if } SScore_a \in (0, 0.7) \\ (+2, \text{“very satisfied”}) & , \text{ if } SScore_a \in [0.7, 1.4) \\ (+3, \text{“the most satisfied”}) & , \text{ if } SScore_a \geq 1.4 \end{cases} \quad (5)$$

note that minimum and maximum scores of  $SScore_a$  are -2 and +2, respectively.

For example,  $SScore_a$  for “speed” in the previous example ( $i = 1$  in Table 3) equals to 1.02. Score level for “speed” is (+2, “very satisfied”). Score levels for all of aspects are shown in the last two columns of Table 3.

Definition 6: Scored aspect knowledgebase (Sakb) is a set which members have an octuple  $\langle a, l_{-3}, l_{-2}, l_{-1}, l_0, l_{+1}, l_{+2}, l_{+3} \rangle$  as shown in (6)

$$Sakb = \langle a_k, l_{-3}, l_{-2}, l_{-1}, l_0, l_{+1}, l_{+2}, l_{+3} \rangle \quad (6)$$

where  $k$  is an index of an aspect (none redundant),  $1 \leq k \leq m$ ,  $m$  is the number of none redundant aspects,  $l_{name}$  is a frequency of score level for aspect  $a_k$ .

Algorithm 1 explains aspect extraction and scoring from a dataset. Line 1 is used to extract aspect and other information by using pattern rules and save into SAOI. Line 2 is used to eliminate irrelevant aspects by using the cosine similarity and Word2Vec. Line 3 is used to initialize Scored Aspect Knowledgebase (Sakb). In lines 4-10, the algorithm scores aspects in SAOI. If an aspect  $a_i$  is not in Sakb, then a new aspect  $a_i$  is added to Sakb.  $l_{number}$  values are equal to 0 for initialization.  $SScore_{a_i}$  is calculated for aspect  $a_i$ . The score level for aspect  $a_i$  ( $SL_{a_i}$ ) is calculated by using  $SScore_{a_i}$  in (5). A frequency of score level for aspect  $a_i$  at  $l_{number}$  value is increased by 1. On line 11, the algorithm returns Sakb.

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**Algorithm 1:** Aspect extraction and scoring
 

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**Input** : Dataset D, Pattern rules, opinion lexicon OL, Word2Vec, SentiWordNet, Intensifier values list

**Output** : Scored Aspect Knowledgebase Sakb =  $\langle a_k, l_{-3}, l_{-2}, l_{-1}, l_0, l_{+1}, l_{+2}, l_{+3} \rangle$

- 1 SAOI  $\leftarrow$  extract aspect, opinion word, and intensifier from D using pattern rules and OL
- 2 SAOI  $\leftarrow$  eliminate irrelevant aspects from SAOI using the cosine similarity and Word2Vec
- 3 Sakb  $\leftarrow \emptyset$
- 4 **for** each aspect  $a_i$  in SAOI **do**
- 5     **if**  $a_i$  is not in Sakb **then**
- 6         add new  $a_i$  to Sakb
- 7          $l_{number} \leftarrow 0$
- 8          $SScore_{a_i} \leftarrow SPol \times [(IV_{iw_i} \times OV) + OV]$
- 9         calculate score level for  $a_i$  ( $SL_{a_i}$ ) by using  $SScore_{a_i}$  in (5)
- 10        increment the  $l_{number}$  of aspect  $a_i$  by one
- 11 **return** the Scored Aspect Knowledgebase (Sakb)

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For example, the *Aspect Extraction and Scoring* algorithm has been applied to Table 3. The result has two tuples. Two aspects of the result are *speed* and *battery*. The Sakb values of  $l_{number}$  for aspect *speed* are  $\langle \text{speed}, 0, 0, 0, 0, 2, 1, 0 \rangle$ . The Sakb values of  $l_{number}$  for aspect *battery* are  $\langle \text{battery}, 0, 1, 0, 0, 1, 2, 0 \rangle$ .

#### 4. RESULT AND DISCUSSION

In this study, we used two benchmark datasets to conduct our experiment. The first dataset [4] has three reviewed domains (computer, speaker, and router). The second dataset [21] has five reviewed domains (Canon camera, MP3 player, Nokia cellphone, Nikon camera, and DVD player). Each reviewed domain is described with the format reviewed\_domain [total of sentences/ total of aspects] as the following: Computer [531/ 354], Speaker [689/ 440], Router [879/ 307], Canon camera [597/ 237], MP3 player [1,716/ 674], Nokia cellphone [546/ 302], Nikon camera [346/ 174], and DVD player [740/ 296].

In our experiment, the result is the scored aspect knowledgebase which is used to represent with graphical charts. In addition, we compare the proposed method with other approaches by using three measures (Precision, Recall, and F1-score) [13, 21]. The formulas are  $Precision = TP/(TP + FP)$ ,  $Recall = TP/(TP + FN)$ , and  $F1\text{-score} = (2 \times P \times R)/(P + R)$ , where  $TP$  is  $|E \cap A|$ ,  $FP$  is  $|E \setminus A|$ , and  $FN$  is  $|A \setminus E|$ . Note that  $E$  is the set of extracted aspects, and  $A$  is the set of annotated aspects in datasets. Figure 2 shows comparisons of the performance experimented with three measures (Precision, Recall, and F1-score). The comparisons are semantic-based product feature extraction (SPE) [9], double propagation (DP) [10], DP+[4], two-fold rule-based model (TF-RBM) [11], sequential pattern rule (SPR) [13], and the proposed AESS. From Figure 2, our proposed method AESS has the highest precision for all of the reviewed domains. In terms of F1-score, the proposed method shows the highest result for Computer, Speaker, Canon camera, and Mp3 player with the values 0.80, 0.74, 0.93, and 0.83, respectively. Furthermore, from AESS system Figure 3 shows some examples of graphical charts for Computer reviewed. Figure 3a shows all aspects score with so so 80%, satisfied 12%, dissatisfied 7%, and the most dissatisfied 1%. Figure 3b shows "screen quality" aspect score with satisfied 75% and dissatisfied 25%.

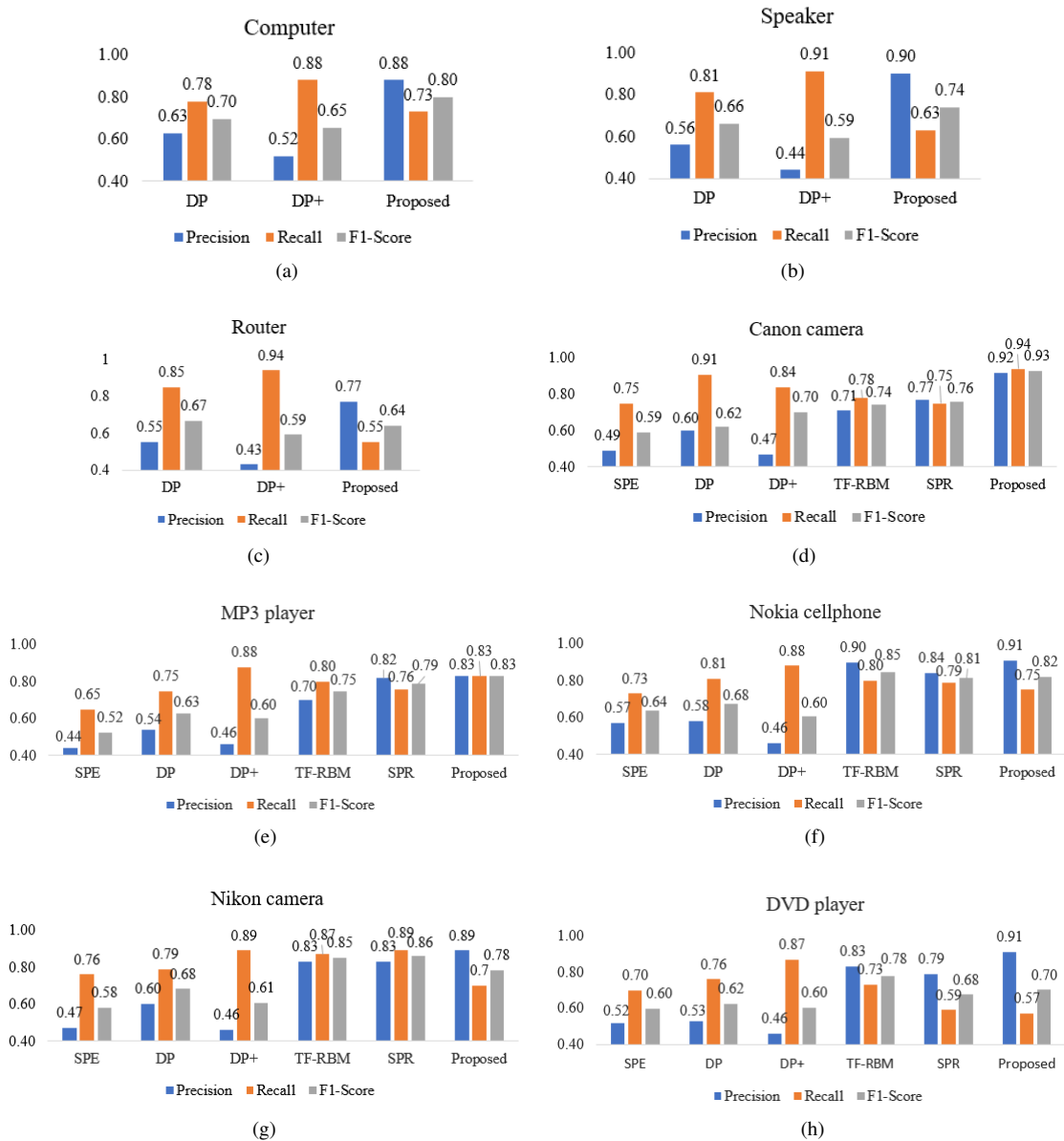


Figure 2. The comparison of approaches for reviewed domains: (a) computer, (b) speaker, (c) router, (d) canon camera, (e) mp3 player, (f) nokia cellphone, (g) nikon camera, and (h) DVD player

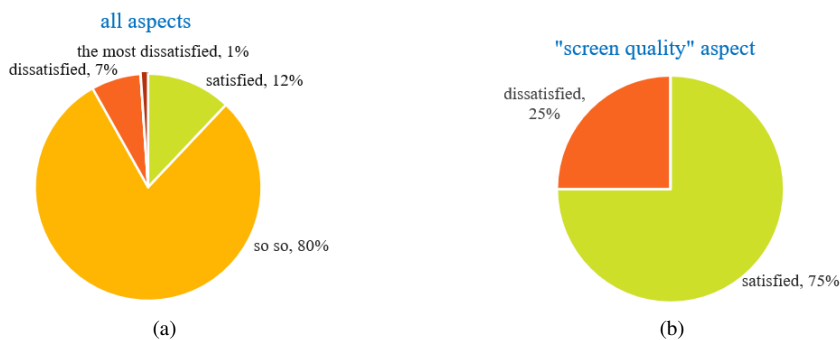


Figure 3. Graphical charts representing for computer reviewed domain: (a) all aspects score and (b) "screen quality" aspect score

## 5. CONCLUSION

Customer satisfaction or dissatisfaction feedback is really important for business intelligent systems. We proposed the new aspect extraction and scoring system (AESS) to represent the satisfaction or dissatisfaction of the consumers in graphical format. The input of the AESS is the textual online data. The output of the AESS is the score of the aspect knowledgebase. The aspect knowledgebase is extracted by using pattern rules and assigned score levels with SentiWordNet. From the benchmark datasets, the proposed AESS has a very high performance when compared to other approaches.

The proposed AESS could be applied to independent domains (e.g., services, products, etc.). Moreover, the proposed AESS does not need any annotated data. In future work, we have a plan to retrieve scores from different lexical resources.

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