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# Attention-based Sentence Extraction for Aspect-based Sentiment Analysis with Implicit Aspect Cases in Hotel Review Using Machine Learning Algorithm, Semantic Similarity, and BERT

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**Abstract:** The development of the aspect-based sentiment analysis (ABSA) method to work on the case of implicit hotel reviews in depth has not been done much. The problem of extracting aspect and opinion words based on syntaxis and semantics is not only influenced by different of sentence structure types but can also be influenced by word sense disambiguation (WSD) level. So, it needs deep attention to solve these problems. For example, the review "*You can't say its cheap because food is cheaper in Chinatown.*", where "*food is cheaper in Chinatown*" is still widely extracted as target terms because there are explicit element of aspect and opinion. In fact, it requires in-depth attention to be able to extract and capture the implicit element "*can't say its cheap*" as a target term. However, there has been not many research that discusses the details of the ABSA process related to this case. Therefore, we propose an attention-based sentence extraction method for ABSA with implicit aspect cases in hotel review. The method purpose is to improve the ABSA accuracy for hotel reviews based on the cases that have not been solved. First, we develop a pre-processing method to the make the data ready to be processed. Then, we build a set rule-based algorithm to get the word types and the relationship of each word in the sentence. These rules function to identify and mark the candidates of aspect and opinion terms based on the review sentence structure types (simple, compound, complex, compound-complex) and to identify and mark the factors that influence the WSD level (conjunction, punctuation, contrast, intensification) in each sentence. The candidates result of aspect and opinion terms are used as input for the aspect categorization process. The aspect categorization process is carried out using machine learning algorithm, implicit aspect corpus, BERT embedding, and semantic similarity to obtain the aspect categories of each review. Furthermore, the ABSA process is carried out using the BERT sentiment analysis method. Finally, the evaluation process for aspect categorization and ABSA are done with the good result. The evaluation result of aspect categorization obtains 91.31% for accuracy, 91.81% for precision, 89.43% for recall, and 90.61% for f1-measure. Meanwhile, the evaluation result of ABSA obtains 98.10% for accuracy, 98.11% for precision, 96.98% for recall, and 97.54% for f1-measure.

**Keywords:** Aspect-based sentiment analysis, Word sense disambiguation, Attention-based sentence extraction, Rule-based algorithm, Machine learning algorithm, BERT, Semantic similarity.

## 1. Introduction

The various methods have been successfully developed to solve problems in the sentiment analysis process for hotel reviews [1-4]. These studies have succeeded in working on cases of explicit and implicit sentences for Sentiment Analysis of hotel reviews. They developed several techniques and methods to solve these cases, starting from the text extraction, aspect categorization (AC) to aspect-based sentiment analysis (ABSA) stages. However, the development of methods to work on implicit review cases in-depth has not been done much.

Previous studies [5, 6] has worked on cases of implicit aspect reviews related to sentence types. These studies has succeeded in showing the characteristics of implicit aspects based on the

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presence or absence of nouns in the review which can be identified by the aspect category keywords. However, the type of implicit commentary that is influenced by the presence of ambiguous sentence factors has not been worked out in this study. These factors consist of negation, contrast transition, or intensifiers [7].

In line with the development of sentiment analysis methods for hotel reviews [8-10], we need a text extraction method that can identify the types of sentences that contain factors that can influence the existence of ambiguous sentences. In sentiment analysis, the text extraction purpose is to extract aspect and opinion terms in the reviews to support the work of the next stage, namely AC and ABSA. The results of pre-processing data which are usually directly processed for the AC process, which consist of only tokens, are certainly not enough to provide accurate results if they are directly processed to determine the category of aspects and the polarity of sentiment in an ambiguous review sentence.

For example, the review "*Room was clean 30 mins later, however - extremely dated and worn out.*", where if it is immediately processed using the AC method [1, 2, 11] then only one aspect category is obtained. Meanwhile, the review should have more than one category of hotel aspects. Then, another example, the review "*You can't say its cheap because food is cheaper in Chinatown.*", where a method is needed that can capture a comparison between the implicit pair of the "*it*" aspect and the opinion "*can't say cheap*" which indicates negative sentiment polarity and pairing the "*food*" aspect with the "*cheaper in Chinatown*" opinion which indicates a positive sentiment polarity. However, there is not many has yet discussed the details of the text extraction, AC, and ABSA processes related to this case.

In the previous discussion [1, 2], the aspect category keywords they used consisted of CLEANLINESS, COMFORT, LOCATION, SERVICE, and FOOD. Each of these categories consists of several variables in the form of nouns and adjectives to be able to extract explicit and implicit aspects. This will certainly affect the error in determining the value of the aspect category from the aspect term obtained. This error occurred because the aspect category keyword in the form of an adjective, which should have been extracted as an opinion term, was instead taken as an aspect term based on the available keywords.

For example, using the keyword exist "good" which is marked manually as the SERVICE aspect category keyword at the AC stage. Based on a review "The only good thing about this hotel was the location!", categories of SERVICE and LOCATION aspects can be produced based on the aspect terms "good" and "location". In fact, the review should be extracted as a LOCATION aspect category based on the aspect term "location" and having the opinion term "good" which gives the polarity value of POSITIVE sentiment. In the condition of determining aspect term keywords, it will certainly cause errors in the text extraction process in determining aspects and opinion terms which will have an impact on inaccurate determination of aspect categories and sentiment polarity. Therefore, a text extraction method is needed to get the right and accurate aspects and opinion terms in hotel reviews [12, 13].

Therefore, we propose a method of attention-based sentence extraction for ABSA with implicit aspect in hotel review using machine learning algorithm, semantic similarity, and BERT. This proposed method aims to improve the accuracy of the ABSA process in hotel reviews based on cases that have not been worked on in previous studies. In early of this research, we develop a proposed pre-processing method so the data is ready to be processed. Specifically, the purpose of this pre-processing method is to identify words and symbols that indicate the sentence structure types (simple, compound, complex, compound-complex) and WSD types (conjunction, punctuation, contrast, intensification) so they are not deleted too. For example, a comma that denotes a type of compound sentence or the word "if" that denotes a contrast factor in the sentence.

Then, we build a set rule-based algorithm to get the word types and the relationship types between the words in the sentence. These rules function to identify and mark the candidates of aspect and opinion terms based on the sentence structure types and the factors that influence the WSD level. These rules purpose to find pairs of aspect and opinion terms that exist in each clause of each sentence type. We determine the criteria for extracted terms pairs in the sentence consist pairs of explicit opinion terms and explicit aspect terms or pairs of explicit opinion terms and implicit aspect terms.

The pairing terms results of aspects and opinion terms are used as input for the AC process. The AC process is carried out using a machine learning algorithm, implicit aspect corpus, BERT embedding, and semantic similarity to obtain the aspect categories in the review. We provide novelty on the development of machine learning methods to be able to extract the aspect category from the implicit aspect terms that exist in the ambiguous sentence. We determine the aspect category based on the pairs of the aspect and opinion terms that exist in the main and subordinate clauses in the sentence.

Furthermore, the ABSA process is carried out using the BERT method. The BERT method determines sentiment analysis by measuring the polarity value of the sentiment in the sentence. The sentiment polarity is carried out based on the results of extracted explicit opinion terms. If there is more than one opinion term, sentiment trends are carried out based on each aspect category that has been generated.

Finally, the evaluation process, we make measurements based on accuracy, precision, recall, and f1-measure to get the success rate of the proposed AC and ABSA methods.

## 2. Related theory

Several theories related to the research are explained in this section.

### 2.1 Dataset

The dataset serves as the main input for testing the proposed method.

### 2.2 Pre-processing

In sentiment analysis, the pre-processing stage is carried out to prepare raw data for the extraction process of aspect and opinion terms. The pre-processing steps [9] consist case folding, filtering, normalization, stop word removal, stemming, and tokenization.

### 2.3 Keyword for aspect categories

In the previous studies [1, 2] about sentiment analysis for explicit aspect extraction, have produced five aspect categories with keyword variables for hotel review.

### 2.4 Text extraction

Text extraction functions to extracts the information that related to the sentence types, word types, and the relationship between words in the sentences. Several methods have also been generated for the text extraction stage using a machine learning algorithm, which is carried out using a rule set to obtain explicit and implicit aspects, and opinion terms candidates too [5, 6, 14, 15]. Text extraction for a review of implicit aspects, requires in-depth attention regarding the structure of the words in the sentence. The sentences that contain implicit aspects that can have an impact on the level of word sense disambiguation can be influenced by several factors [7] consist: negation (conjunction analysis and punctuation marks); contrast transition; and intensifiers. One of the factors that can affects the level of disambiguity of a sentence so impact on error in extracting the aspect term.

### 2.5 Semantic similarity

Semantic similarity purposes to measure the comparative value of similarity between words based on semantic concept relationships using semantic similarity metrics [16]. One method that is often used to measure semantic similarity, cosine similarity [17], works by determining the degree of similarity between sentence 1 (S1) and sentence 2 (S2) by calculating the number of terms that are similar in both. The used word vector to measure cosine similarity is shown in Eq. (1).

$$Cosine(S1, S2) = \frac{\sum_{i=1}^{k} S1i\, S2i}{\sqrt{\sum_{i=1}^{k} S1i^2}\sqrt{\sum_{i=1}^{k} S2i^2}} \qquad (1)$$

### 2.6 BERT

Bidirectional encoder representations from transformers (BERT) is a modeling method that is widely used for understanding language. BERT is designed to train deep two-way representation of unlabeled text by co-conditioning the left and right contexts across all layers. There are two steps in the BERT framework, namely pre-training and fine-tuning. Initially, for the pre-training process, a corpus of 3,300 million words was used. Then, the fine-tuning process functions to model single text extraction tasks or text pairs by swapping the appropriate input and output. For applications involving text pairs, BERT uses the self-attention mechanism to encode the combined text pairs by effectively implementing the self-attention mechanism that simultaneously includes two-way cross-attention between two sentences [18].

### 2.7 Evaluation

The evaluation process works by using confusion matrix [19], as shown in Table 1, to measure and calculate the scores of precision, recall, f1-measure, and accuracy of aspect categorization and aspect-based sentiment analysis.

## 3. Research method

This research begins by preparing a hotel review dataset. This dataset is pre-processed so that it is ready to be processed. Then, text extraction, aspect

Table 1. Confusion matrix

| | | Predicted Class | |
|---|---|---|---|
| | | **Positive** | **Negative** |
| **Actual Class** | **Positive** | True Positive (TP) | False Negative (FN) |
| | **Negative** | False Positive (FP) | True Negative (TN) |

Table 2. Dataset representation

| Review ID | Review |
|---|---|
| 0 | The only good thing about this hotel was the location! |
| 1 | Room was clean 30 mins later, however - extremely dated and worn out. |
| 2 | You can't say its cheap because food is cheaper in Chinatown. |

categorization (AC), and aspect-based sentiment analysis (ABSA) are performed. Finally, the evaluation process is carried out.

### 3.1 Dataset

The representation of the dataset that we use is shown in Table 2. We use the hotel review dataset [1, 2] due to the following background:

1. The dataset consists of reviews that contain explicit and implicit aspects that have not yet been discussed about the extraction process and results.
2. The dataset includes word sense disambiguation problems that can affect the extraction of implicit aspect terms.
3. The dataset consists of reviews that can contain one or more words, explicit and implicit aspects.

### 3.2 Keyword extraction for aspect category

We developed the aspect category keywords [1, 2] by manually removing some of the variables in the form of adjectives in order to better extract explicit and implicit aspects. This is because if an adjective is included in the aspect category keyword, it will certainly affect the determination of the aspect category value from the aspect term results obtained. In the FOOD aspect category, we remove the keyword "delicious". In the LOCATION aspect category, we remove the keywords "far" and "close".

Table 3. Proposed keywords for aspect categories

| Aspect Categories | Variable |
|---|---|
| Cleanliness | ventilation, cleanliness, smell, cobweb, smoke, carpet, laundry, furniture, wall, housekeeping, toilet. |
| Comfort | connection, sleep, meeting, charge, activity, bedroom, comfort, feel. |
| Food | cafe, drink, breakfast, spicy, meal, bagel, tea, buffet, bar, waffle, restaurant, dinner, lunch, brunch, food, dish, wine, salad, coffee, pastry, menu, item, cup. |
| Location | location, railway, view, station, airport, distance, convenient, train, metro, place, mall. |
| Service | facility, desk, reliable, convenient, wi-fi, internet, staff, reliable, pool, parking, conference room, fee, gym. |

Table 4. Pre-processing algorithm

| |
|---|
| *Input: Hotel Dataset* |
| 1. *Taking the text review as an input* |
| 2. *Converting into Lowercase* |
| 3. *Spelling Correction* |
| 4. *Remove Punctuation* |
| 5. *Stemming* |
| 6. *Lemmatization* |
| 7. *Save the results of preprocessing* |

Then, in the SERVICE aspect category, we removed the keywords "fast", "good", "polite", "helpful", "friendly", and "quick". The proposed keywords for aspect categories are shown in Table 3.

### 3.3 Pre-processing

In the pre-processing stage, we convert the dataset into lower case form. Then, we did spelling correction. Then, we performed the removing punctuation. Specifically for the step of removing punctuation, we do not remove some symbols indicating a type of sentence as a basis for preparation for the next stage. These symbols include: period, comma, dash, colon, semicolon, exclamation, and question. Meanwhile, for the abbreviations Mr., Ms., Mrs., and .com we have omitted them. Finally, we save the results of pre-processing into the local directory. The proposed pre-processing algorithm is shown in Table 4. Then, the proposed pre-processing results for 3 reviews are shown in Table 5.

In the Table 5, the result of the review of ID [0] shows that the word "the" has been removed. Then, the result of the ID review [1] shows that there is no

Table 5. Proposed pre-processing results

| Rev. ID | Review | Proposed Pre-processing Result |
|---|---|---|
| 0 | The only good thing about this hotel was the location! | [‘only’, ‘good’, ‘thing’, ‘about’, ‘this’, ‘hotel’, ‘was’, ‘location’, ‘!’] |
| 1 | Room was clean 30 mins later, however - extremely dated and worn out. | [‘room’, ‘was’, ‘clean’, ‘30’, ‘mins’, ‘later’, ‘,’ ‘however’, ‘-‘, ‘extremely’, ‘dated’, ‘and’, ‘worn’, ‘out’, ‘.’ |
| 2 | You can't say its cheap because food is cheaper in Chinatown. | [‘you’, ‘can’, ‘n't’, ‘say’, ‘it’, ‘is’, ‘cheap’, ‘because’, ‘food’, ‘is’, ‘cheaper’, ‘in’, ‘Chinatown’, ‘.’ |

deletions or changes to any words. Meanwhile, the result of the ID review [2] shows that the word "can't" is converted into "can" and "n't". Furthermore, the word "its" is converted into "it" and "s".

### 3.4 Attention-based sentence extraction

At the text extraction stage, we implemented the proposed attention-based sentence extraction method to be able to solve the problem of aspect and opinion extraction, especially in sentences that contain implicit aspects because there are factors that affect the level of word sense disambiguation. The attention-based sentence extraction flowchart is shown in Fig. 1. The attention-based sentence extraction algorithm is shown in Table 6. For instance, this algorithm implementation for the review ID [2] is shown in Table 7. The following describes the details of the attention-based sentence extraction stages.

First, the pre-processing results are used as input for the splitting sentence process based on full stops, exclamation points, and question marks at the end of the sentence. The results of this sentence separation are indexed based on review ID.

Second, the POS tagging process is carried out to label each word according to its type.

Third, the parsing process is carried out to identify the factors that affect the level of word sense disambiguation. In this process, we use the chunking feature to extract terms in the form of single words or phrases based on word order, where NN with NN adjacent to each other indicates a noun phrase and RB with JJ adjacent to each other indicates an adjective phrase. Then, we use the dependency parse feature to extract terms that contain word sense disambiguation sub-factors based on word relations as follows:

1. Conjunction is denoted by:
    a. Conj relation
    The conj relations marked as conjunctions are: the conj relations between two aspect terms which are denoted by the conj between two NNs; and the relation conj between two opinion terms denoted by conj between two JJs.
    b. Punct relation on target comma
    Punct relations in the target comma marked as a conjunction, namely: if there is a comma that separates a sentence into two or more clauses; and if there is a comma separating more than one NN or JJ.

    Conjunction analysis aims to capture the presence of more than one candidate aspect or opinion term in a sentence.
2. Punctuation is denoted by:
    a. Punct relation on the exclamation mark target.
    This analysis aims to capture the existence of expressions or statements in the form of exclamations or orders that describe sincerity, extraordinaryness, or emotional strength representing an opinion term towards a target aspect term.
    b. The punct relation on the target question mark.
    This analysis aims to capture expressions or statements in the form of doubts about the truth of a statement that represents an opinion term against a target aspect term.
3. Contrast is denoted by the relation of advcl and dep.
    This analysis aims to capture the existence of opinion terms that give less or opposite value to the existing aspect terms. We use variable contrast in the algorithm, which consists of: comparatively; different from; even though; however; although; conversely; instead; in comparison; nevertheless; in contrast; however; yet; on the other hand; on the contrary; other hand; outside of; besides; otherwise; but.
4. Intensification is denoted by advmod relation.
    This analysis aims to capture the existence of opinion phrases that indicate strong and weak emotions. We use a variable intensifier in the algorithm, which consists of: almost; completely; barely; quite; somewhat; fairly; incredibly; enough; in large part; scarcely; badly; little; less; least; just; purely; profusely; too; very; extremely; horribly; unusually; wonderfully; deeply; absolutely; completely;

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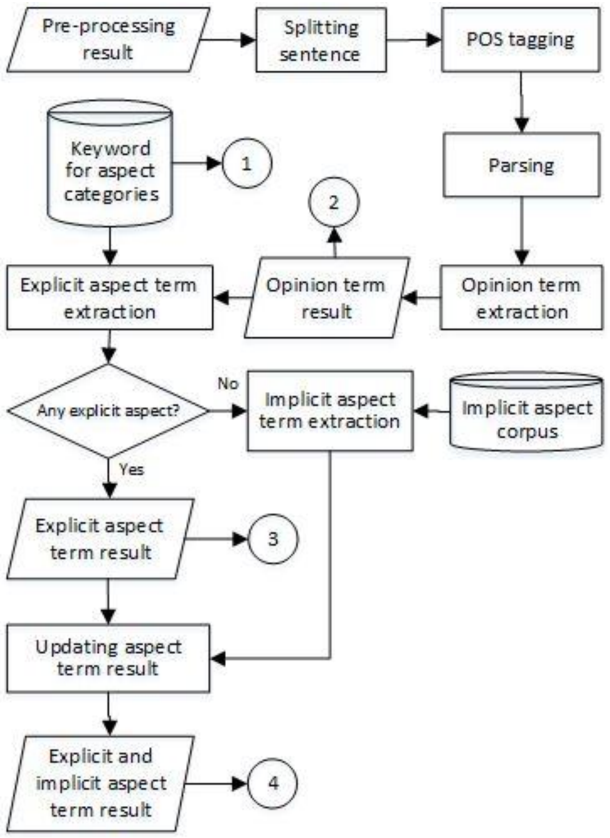


Figure. 1 Attention-based sentence extraction flowchart

Table 6. Attention-based sentence extraction algorithm

| |
|---|
| *Input: Pre-processing result, contrast, intensifier* |
| 1. Taking the pre-processing result as the input. |
| 2. Split the review into sentence based on full stops, exclamation points, and question marks. |
| 3. POS Tagging. |
| 4. Extract word type and words relationship using enhanced++ dependency parse. |
| 5. Conjunction analysis. |
| 6. Punctuation analysis. |
| 7. Contrast analysis. |
| 8. Intensifier analysis. |
| 9. Extract explicit opinion terms based on words that labelled as JJs. |
| 10. Extract explicit aspect terms based on words that labelled as NNs and aspect keywords. |
| 11. Extract implicit aspect terms based on words that are contained in implicit aspect corpus. |
| 12. Save the results. |

hardly; really; pretty; really; insanely; remarkably; greatly; highly; most; much; intensely; strongly; utterly.

Fourth, the process of extracting explicit opinion terms is carried out by taking terms that have the JJ tag label.

Fifth, the process of extracting explicit and implicit aspect terms. The explicit aspect term extraction process is carried out by taking terms that have NN tag labels that can be identified using the aspect keyword. Meanwhile, if not, then we mark NN as an implicit aspect term. In addition, identification of implicit aspect terms is carried out by identifying each existing explicit opinion term using the corpus implicit aspect.

Finally, all the results of the pair of aspects and opinion terms for each review are stored in the local directory based on the relationship rules between aspects and opinion terms. Then, these pairing results of explicit aspect and opinion terms are used as the input for aspect categorization 2. Meanwhile, the pairing results of explicit and implicit aspect terms and also explicit opinion terms are used as the input for aspect categorization 3.

Table 7. Attention-based sentence extraction example

| Steps | Results |
|---|---|
| Taking the input | you can n't say it is cheap because food is cheaper in chinatown. |
| Split the review | you can n't say it is cheap because food is cheaper in chinatown. |
| POS Tagging | you <PRP> can <MD> n't <RB> say <VB> it <PRP> is <VBZ> cheap <JJ> because <IN> food <NN> is <VBZ> cheaper <JJR> in <IN> chinatown <NNP> .<.> |
| Extract type and relationship of words | nsubj(say, you), aux(say, can), advmod(say, n’t), punct(say, .), ccomp(say, cheap), nsubj(cheap, it), cop(cheap, is), advcl:because(cheap, cheaper), mark(cheaper, because), nsubj(cheaper, food), cop(cheaper, is), obl:in(cheaper, chinatown), case(chinatown, in) |
| Conjunction analysis | - |
| Punctuation analysis | punct(say, .) |
| Contrast analysis | advcl:because(cheap, cheaper), |
| Intensifier analysis | - |
| Opinion term extraction | “cheap”, “cheaper” |
| Explicit aspect term extraction | null, food |
| Implicit aspect term extraction | cheap, null |
| Pairing result of aspect and opinion terms | [cheap:”n’t cheap”], [food:”cheap”] |

### 3.5 AC

At the AC stage, we aim to obtain aspect

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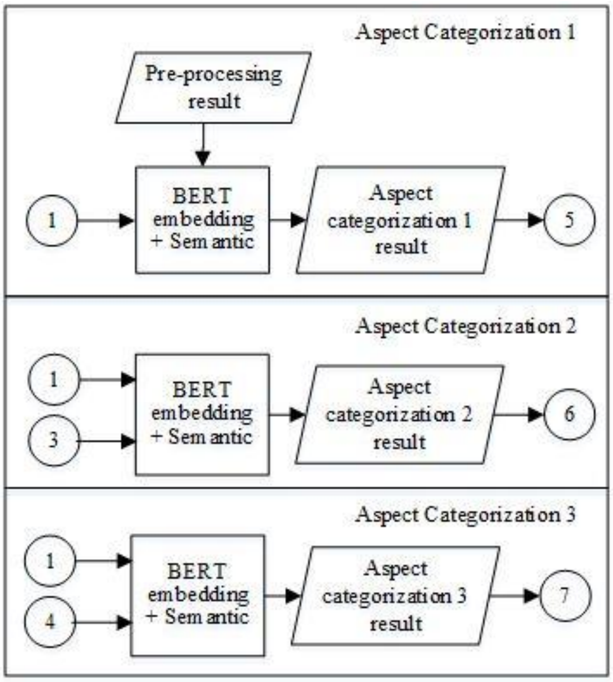


Figure. 3 Aspect categorization process

categories based on the terms of the explicit and implicit aspects of the existing reviews from the results of structure-based sentence extraction. The aspect categories consist location, cleanliness, comfort, food, and service. We use the BERT embedding and semantic similarity methods for this aspect categorization stage. Then, to get the best performance aspect categorization, we tested this stage with three AC approaches, namely AC1, AC2, and AC3.

Aspect categorization 1 use pre-processing result as the input. Aspect categorization 2 use pairing results of explicit aspect and opinion terms as the input. The stages of the aspect categorization process are shown in Fig. 3. Aspect categorization 3 use the pairing results of explicit and implicit aspect terms and also explicit opinion term as the input. The stages of the aspect categorization process are shown in Fig. 3.

Each of these aspect categorization approaches measures word similarity between their input and aspect keywords to determine the aspect category for each review. If the extracted terms denote an aspect category, then the aspect category is taken based on the average word similarity value of all existing terms. However, if the extracted terms denote some aspect categories, then all result of aspect categories are taken.

### 3.6 ABSA

ABSA stage purpose is to obtain polarity of sentiment based on the results of the opinion terms

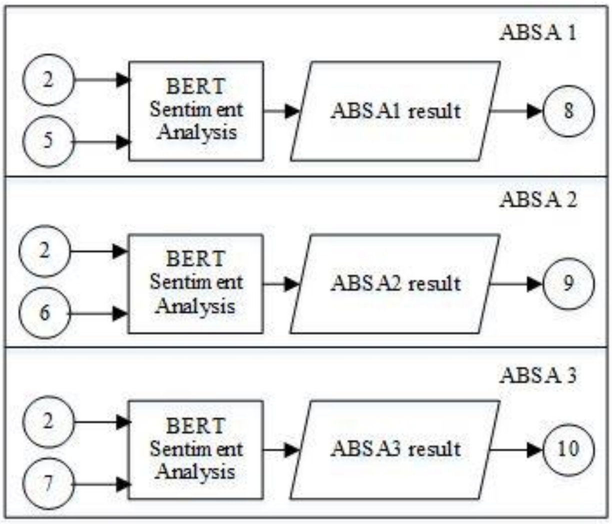


Figure. 4 ABSA process

that have been obtained and based on the aspect category pair. This stage categorizes the sentiment polarity into two, namely positive and negative. We use the BERT sentiment analysis method for this stage. ABSA testing is carried out on each output of the 3 Aspect Categorization processes to find out how the performance of the proposed method is compared to existing methods. ABSA1, ABSA2, and ABSA3 are methods used to measure the polarity of sentiment, respectively, from the results of AC1, AC2, and AC3.

### 3.7 Evaluation

In the evaluation stage, the accuracy (A), precision (P), recall (R), and F1-measure (F) values are calculated based on the confusion matrix with the following equation.

$$A = \frac{TP+TN}{TP+FP+TN+FN} \tag{2}$$

$$P = \frac{TP}{TP+FP} \tag{3}$$

$$R = \frac{TP}{TP+FN} \tag{4}$$

$$F = \frac{2 \times P \times R}{P + R} \tag{5}$$

## 4. Result and analysis

In this section, we present the analysis and results of the proposed text extraction, aspect categorization (AC), and ABSA methods.

### 4.1 Attention-based sentence extraction result

The results of the text extraction stage using attention-based sentence extraction are shown in

Table 8. Attention-based sentence extraction result

| Rev. ID | Sent. ID | Aspect Term | | Opinion Term | |
|---|---|---|---|---|---|
| | | i | ii | i | ii |
| 0 | 0 | location | location | good | good |
| 1 | 0 | room | room | clean, extremely dated, worn out | clean, extremely dated, worn out |
| 2 | 0 | null, food | cheap, food | n't cheap, cheap | n't cheap, cheap |

NB: i. doing by expert; ii. Doing by algorithm

Table 5.

Reviews with ID 0:0, can be extracted aspect term "location" and opinion term "good". Reviews with an ID of 1:0 can be extracted in the aspect term "room" and the opinion terms "clean", "extremely dated", and "worn out". Based on the results done by the expert, the two reviews can still be extracted properly using the Rachmad rule algorithm [6], Suhariyanto [5], and the proposed text extraction method. However, Rachmad [6], Suhariyanto [5] have not been able to properly extract the 2:0 ID review, where both of them produce the aspect term "food" and the opinion term "cheap". The two methods failed to get the aspects and opinion terms that were in accordance with what was done by the expert. While the proposed method of text extraction can extract well the results of the aspect terms "cheap" and "food" and the opinion terms "n't cheap" and “cheap”.

The result of this text extraction shows significant result, where the element of the implicit aspect that is contained in ambiguous sentence can be identified and extracted. The pairing result of aspect and opinion terms in ID review [0] is [location:”good”]. The pairing result of aspect and opinion terms in ID review [1] is [room:”clean”, ”extremely dated”, ”worn out”]. The pairing results of aspect and opinion terms in ID review [2] are [cheap:”n’t cheap”] and [food:”cheap”].

### 4.2 Aspect categorization result

The aspect categorization (AC) result obtain three results of AC performances: AC1, AC2, and AC3.

- **AC 1**

The results of aspect categorization 1 (AC1) using BERT embedding and semantic similarity are shown in Table 6. Table 6 shows the AC1 can extract the aspect terms in five aspect categories. The obtained results are based on the highest similarity value between aspect terms and aspect categories

Table 9. AC1 result

| ID | Terms | Aspect categories | | | | |
|---|---|---|---|---|---|---|
| | | 1 | 2 | 3 | 4 | 5 |
| 0 | good, hotel, location | 0.7178 | 0.7738 | 0.8213 | 0.8190 | 0.7467 |
| 1 | room, clean, 30, mins, extremely, dated, worn, out | 0.7695 | 0.7959 | 0.7798 | 0.8351 | 0.7579 |
| 2 | N’t, say, cheap, food, cheaper, chinatown | 0.7501 | 0.7785 | 0.7931 | 0.8163 | 0.7687 |

NB: 1.Cleanliness; 2.Comfort; 3.Location; 4.Service; 5.Food.

Table 10. AC2 result

| ID | Terms | Aspect categories | | | | |
|---|---|---|---|---|---|---|
| | | 1 | 2 | 3 | 4 | 5 |
| 0 | location, good | 0.5740 | 0.6180 | 0.6836 | 0.6671 | 0.5779 |
| 1 | room, clean | 0.7246 | 0.6884 | 0.6684 | 0.7226 | 0.6160 |
| | room, extremely dated | 0.6798 | 0.7158 | 0.7106 | 0.7582 | 0.6632 |
| | room, worn out | 0.6471 | 0.6744 | 0.6629 | 0.7053 | 0.6084 |
| 2 | null, n’t cheap | 0.5756 | 0.6208 | 0.6507 | 0.6782 | 0.5957 |
| | food, cheaper | 0.6147 | 0.6453 | 0.6709 | 0.6964 | 0.7232 |

NB: 1.Cleanliness; 2.Comfort; 3.Location; 4.Service; 5.Food

keywords. For review [0], the result of aspect category is LOCATION with a value of 0.8213. For review [1], the result of aspect category is SERVICE with a value of 0.8351. For review [2], the result of aspect category is SERVICE with a value of 0.8163.

- **AC 2**

The results of aspect categorization 2 (AC2) using BERT embedding and semantic similarity are shown in Table 7. Table 7 shows the AC2 can extract the aspect terms in five aspect categories. The results of the aspect categories obtained are based on the highest similarity values between the aspect terms and the aspect categories keywords.

For review [0], the result of aspect category is LOCATION with value of 0.6836. For review [1], the results of aspect categories are CLEANLINESS, SERVICE, and SERVICE with values 0.7246, 0.7582, and 0.7053. The final results of aspect categories are 0.7246 for CLEANLINESS and

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Table 11. AC3 result

| ID | Terms | Aspect categories | | | | |
|---|---|---|---|---|---|---|
| | | 1 | 2 | 3 | 4 | 5 |
| 0 | location, good | 0.5740 | 0.6180 | 0.6836 | 0.6671 | 0.5779 |
| 1 | room, clean | 0.7246 | 0.6884 | 0.6684 | 0.7226 | 0.6160 |
| | room, extremely dated | 0.6867 | 0.7578 | 0.7159 | 0.7523 | 0.6614 |
| | room, worn out | 0.6471 | 0.6744 | 0.6629 | 0.7053 | 0.6084 |
| 2 | cheap, n't cheap | 0.5910 | 0.6521 | 0.6273 | 0.6596 | 0.6642 |
| | food, cheaper | 0.6147 | 0.6453 | 0.6709 | 0.6964 | 0.7232 |

NB: 1.Cleanliness; 2.Comfort; 3.Location; 4.Service; 5.Food

Table 12. Result of AC performances

| AC Performances | | |
|---|---|---|
| **ABSA Approach** | **Method** | **F1-Measure** |
| AC1 | BERT embedding, semantic similarity | 0.75 |
| AC2 | Machine learning algorithm, BERT embedding, semantic similarity | 0.82 |
| **AC3** | Machine learning algorithm, implicit aspect corpus, BERT embedding, semantic similarity | **0.91** |

0.7318 for SERVICE. For review [2], the results of aspect categories are SERVICE and FOOD with values 0.6782 and 0.7232.

- **AC 3**

The results of aspect categorization 3 (AC3) using BERT embedding and semantic similarity are shown in Table 8. Table 8 shows the AC3 can well extract the aspect terms in five aspect categories. The results of the obtained aspect categories are based on the highest similarity values between the aspect terms and the aspect categories keywords.

For review [0], the result of aspect category is LOCATION with a value of 0.6836. For review [1], the results are CLEANLINESS, COMFORT, and COMFORT with values 0.7246, 0.7578, and 0.6744. The final results of aspect categories for review [1] are 0.7246 for CLEANLINESS and 0.7161 for COMFORT. For review [2], the results are FOOD and FOOD with values 0.6642 and 0.7232. The final result of aspect category for review [2] is 0.6937 for FOOD. The obtained results by AC3 are effective because it can determine the appropriate aspect category based on the meaning of the implicit aspect terms that are contained in the sentences.

Table 9 shows the evaluation results for the f-1 measure from the 3 aspect categorization performances: AC1, AC2, and AC3. The f-1 measure result of proposed aspect categorization method (AC3) is 0.91 and it is indicating that this proposed method is better than AC1 and AC2 with value of 0.75 and 0.84 respectively.

### 4.3 Aspect-based sentiment analysis result

The ABSA proposed method can work better and more accurately to extract explicit and implicit aspects in the documents. The ABSA comparison results between ABSA1, ABSA2, and proposed method (ABSA3) are shown in Table 10. The opinion term extraction works automatically to classify sentiments into positive and negative. ABSA1, ABSA2, and ABSA3, which respectively work based on the results of AC1, AC2, and AC3, were conducted as the pairing of sentiment polarity in each review from extracted opinion terms.

ABSA1 works by using the AC1 and extracted opinion terms results as the input. In IDRreview [0:0], the extracted opinion term “good” is immediately processed to obtain a sentiment polarity class for the result of the aspect category **LOCATION**. The obtained sentiment polarity result is **Positive**. In IDRreview [1:0], the extracted opinion term “clean” can obtain the sentiment polarity **Positive** for the aspect category **SERVICE**. In IDRreview [2:0], the extracted opinion terms “cheap” and “cheaper” can obtain the sentiment polarity **Positive** for the aspect category **SERVICE**.

ABSA2 works by using the AC2 and extracted opinion terms results as the input. In IDReview [0:0], the extracted opinion term “good” is immediately processed to obtain a sentiment polarity class for the result of the aspect category **LOCATION**. The obtained sentiment polarity result is **Positive**. In IDReview [1:0], the pairs result of aspect categories and opinion terms [CLEANLINESS: “clean”] and [SERVICE: “extremely dated”, “worn out”] can obtain sentiment polarities **Positive** and **Negative**. In IDReview [2:0] the pairs result of aspect categories and opinion terms [SERVICE: “not cheap”] and [FOOD: “cheaper”] can obtain sentiment polarities **Negative** and **Positive**.

ABSA3 works by using the AC3 and extracted opinion terms results as the input. As well as ABSA1 and ABSA2, in IDReview [0:0], the extracted opinion term “good” is immediately processed to obtain a

Table 13. ABSA comparison result

| Review | Opinion Extracted | ABSA result | |
|---|---|---|---|
| | | AC | Sentiment |
| the only good thing about this hotel was the location! | good | ABSA1 | |
| | | Location | Positive |
| | good | ABSA2 | |
| | | Location | Positive |
| | good | **ABSA3** | |
| | | **Location** | **Positive** |
| room was clean 30 mins later, however - extremely dated and worn out. | clean | ABSA1 | |
| | | Service | Positive |
| | clean, extremely dated, worn out | ABSA2 | |
| | | Cleanliness Comfort | Positive Negative |
| | clean, extremely dated, worn out | **ABSA3** | |
| | | **Cleanliness Comfort** | **Positive Negative** |
| you can't say its cheap because food is cheaper in chinatown. | cheap, cheaper | ABSA1 | |
| | | Service | Positive |
| | n’t cheap, cheaper | ABSA2 | |
| | | Service Food | Negative Positive |
| | n’t cheap, cheaper | **ABSA3** | |
| | | **Food** | **Negative** |

Table 14. Comparison of ABSA performances result

| ABSA Performances | | | | |
|---|---|---|---|---|
| **ABSA Approach** | **P** | **R** | **F** | **A** |
| Reza [1] | 0.91 | 0.96 | 0.93 | - |
| Dewi [2] | 0.93 | 0.96 | 0.95 | - |
| Deny [3] | 0.96 | 0.98 | 0.97 | 0.94 |
| Pulung [4] | 0.96 | 0.98 | 0.97 | 0.97 |
| **Proposed method** | **0.98** | **0.97** | **0.98** | **0.98** |

sentiment polarity class for the result of the aspect category **LOCATION**. The obtained sentiment polarity result is **Positive**. In IDReview [1:0], the pairs result of aspect categories and opinion terms [CLEANLINESS: “clean”] and [COMFORT: “extremely dated”, ”worn out”] can obtain sentiment polarities **Positive** and **Negative**. In IDReview [2:0], the pair result of aspect category and opinion term [FOOD: “not cheap”] can obtain sentiment polarity **Negative**.

Table 13 shows the comparison of ABSA performances result between the ABSA proposed method and the ABSA previous studies [1-4]. The ABSA proposed method (ABSA3) can work better than the ABSA previous studies with score: 0.98 for precision (P), 0.97 for recall (R), 0.98 for F-1 measure (F), and 0.98 for accuracy (A).

## 5. Conclusion

This research proposes attention-based sentence extraction for aspect-based sentiment analysis with implicit aspect cases in hotel review using machine learning algorithm, semantic similarity, and BERT.

We present a proposed text extraction method using attention-based sentence extraction approach to identify the level of disambiguity in a review from the analysis of sub-factor conjunctions, punctuation, contrast, and intensification. As we have presented, the level of disambiguity of a review can affect the misjudgment of aspect categorization and aspect-based sentiment analysis. Therefore, we built a text extraction method to captures the sub factor elements of word sense disambiguation, explicit opinion terms, explicit aspect terms, and implicit aspect terms. The cases that we work on are not only limited to sentences that containing single aspect and opinion terms, but also sentences that containing multi aspect and opinion terms.

Reza [1], Dewi [2], and Pulung [4] can solve the extraction cases of implicit aspect terms but they are still work in disambiguous sentence cases. We can solve the existing extraction cases better than them. We are not only extract implicit aspect terms in the disambiguous sentence cases but also extract implicit aspect terms in the ambiguous sentence. Then, the proposed text extraction result is used as the input for proposed methods of aspect categorization and ABSA.

The evaluation results of proposed aspect categorization and proposed ABSA are better than these previous studies. The proposed aspect categorization method (AC3) performance value with F1-measure of 0.91 shows that AC3 performance is better than AC1 and AC2. The evaluation result AC3 obtains 91.31% for accuracy, 91.81% for precision, 89.43% for recall, and 90.61% for f1-measure.

Meanwhile, the evaluation result of proposed ABSA (ABSA3) can determine the sentiment polarity of each aspect category in the review better than ABSA1 and ABSA2. The evaluation result of proposed ABSA method (ABSA3) obtains 98.10% for accuracy, 98.11% for precision, 96.98% for recall, and 97.54% for f1-measure.

In this research, we have not worked on in-depth cases of text extraction, such as cases of homonym and polysemy. For further research, it is necessary to develop ABSA method that related to these cases. We hope that the proposed method and the results we get

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can be useful as well as used for the next development methods, especially not only in hotel reviews but also in other reviews. This proposed method also needs to be combined or changed with other aspect categorization and sentiment analysis methods in order to increase the accuracy of these processes.

## Conflict of interest

The authors declare no conflict of interest.

## Author contributions

This research can work well and successfully because of the following research contributions: Conceptualization by Budi Harjo and Muljono; Methodology by Muljono and Budi Harjo; Software usage by Budi Harjo and Rachmad Abdullah; Validation, formal analysis, investigation, resources by Budi Harjo and Muljono; Data curation by Rachmad Abdullah; Writing-original draft preparation, and writing-review and editing by Rachmad Abdullah and Muljono; Visualization by Budi Harjo; supervision by Muljono; and Project administration and funding acquisition by Budi Harjo and Muljono.

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