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Aspect Based Sentiment Analysis: A Systematic Literature Review

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Abstract—Aspect based sentiments can provide more detailed information about the sentiment (positive, negative, and neutral) based on an aspect in a review. It can provide better recommendations to users in decision making process. A number of previous studies have been conducted on aspect-based sentiment analysis indicating that survey is needed to provide an overview of the method available in aspect-based sentiment analysis. The survey method has been implemented since the last 5 years to obtain novelty from existing methods. The Systematic Literature Review (SLR) method is used to review a collection of 34 papers from various academic databases which focus on the aspect of extraction, sentiment analysis, and aspect aggregation. The papers will be sorted based on the focus of the method used. For each analysis, a detailed analysis is described on the contribution of the method to the aspect-based sentiment analysis alongside a comparison with other methods as well as advantages and disadvantages. The last section discusses the method commonly used in this study as well as future challenges in the study focusing on aspect-based sentiment analysis.

Keywords—sentiment analysis, systematic literature review, aspect-based sentiment analysis

1. INTRODUCTION

The rapid development in this digital age has caused an explosion of information. This information can have a positive impact on users, for example product review. Sentiment analysis can provide recommendations by taking the opinion of a review from other users. This recommendation will accommodate users if it is presented based on criteria that the user desires or is called the aspect-based sentiment analysis [1]; for example, a review "*The screen is very colorful especially for an LCD screen*" discusses a screen aspect which is associated with opinion word *colorful* that contain positive meaning.

Generally, aspect-based sentiment analysis is divided into several sub-processes: aspect detection, sentiment analysis, and aspect aggregation [2]. Aspect detection is the process of detecting and obtaining the aspect of an opinion. The aspect can be explicitly contained in the opinion or implied in the sentence [3]. In addition, a number of reviews contain an aspect without an opinion so the aspect is called objective aspect; for example, a review "*If the phone would have a better connection to 4G networks in my location I would keep this phone hands down*" does not contain any opinion but there is a suggestion expected by the reviewer, so that the aspect is an objective aspect. Sentiment analysis is the process of determining sentiment attached to that aspect of which opinion usually belongs to a particular domain; for example, a review "*battery life of this phone is very long*" contains a positive opinion in the word *long* which belongs to the *smart phone* domain. However, a review "*The program X takes very long to finish the process*" contains a negative opinion in the word *long* which belongs to the *application* domain. Thus, it is highly important to pay attention to the domain and context in determining the sentiment of an aspect. Furthermore, aspect aggregation is a process of grouping each aspect from the previous process and is presented in summary which can provide recommendations for users [4], for example, reviews" *The image taken with this camera is very good*" and "*Sony's camera has better picture quality than Nikon's camera*" contain aspects of *image* and *picture*; both aspects can be combined into one due to the same meaning, that is *image*.

In this study, we conducted Systematic Literature Review (SLR) to collect and analyze the latest academic insights on aspect-based sentiment analysis. This study is divided into a number of sections. Section 2 describes the research method. Section 3 explains the findings obtained based on the proposed research method. Moreover, the discussion of the grouping of the aspect-based sentiment analysis method is described in detail in Section 4. Last but not least, Section 5 is the conclusion of the study.

2. RESEARCH METHOD

In this study, we used the Systematic Literature Review (SLR) method, which is considered to be reliable, in-depth, and accountable [5, 6]. The guideline of the SLR method is proposed by Kitchenham [5, 7]. The method begins by formulating research questions followed by finding relevant studies in the database. The results of the paper are sorted based on the inclusion and exclusion criteria then the paper is reviewed and analyzed to answer the research question.

2.1 Research Question

This study generally aims to obtain an overview of the current academic insights about Aspect-Based Sentiment Analysis. Furthermore, we also elaborate on a question to answer the sub-processes in Aspect-Based Sentiment Analysis. Hence, the research question raised in this paper is: How is the grouping methods in the aspect-based sentiment analysis?

2.2 Search and Selection Process

a) Database

Keywords are used to find relevant articles in the academic database. In this study, we selected 3 databases as presented in Table 1.

Table 1. Academic database

Code	Publisher	Database	Link
Spr	Springer	Springer Link	https://link.springer.com/
Sci	Elsevier	Science Direct	https://www.sciencedirect.com/
Ieee	IEEE	IEEE Explore	https://ieeexplore.ieee.org/Xplore/home.jsp

b) Filter 1

The first filter is done automatically by searching the database with the following queries and limitations which aim to answer the research question that searching word phrases is conducted by finding relevant articles in the academic database. To expand, we also use synonyms of the word phrase. Therefore,the queries and limitations are:

- Query String: aspect AND (sentiment analysis OR detection OR extraction OR aggregation OR grouping OR sentiment classification OR semantic sentiment OR context sentiment OR opinion mining)
- Timespan: 2013 – 2019
- Language: English
- Reference Type: Journal, Conference

c) Filter 2

The result of the first filter was automatically extracted in terms of title, abstract, and keywords which shared query string in Filter 1.

d) Filter 3

Due to the fact that automatic search process resulted in many irrelevant studies, the next process is to do a manual selection to obtain relevant studies in accordance with the specified inclusion and exclusion criteria. For practical reasons and in accordance with the guidelines [7], this process was conducted in 2 phases. First, the inclusion and exclusion criteria were assessed solely based on the title, abstract, and keywords. Second, the inclusion and exclusion criteria were re-evaluated based on the full text.

The inclusion criteria are:

- The study must discuss one of the aspect-based sentiment analysis tasks, be it aspect detection, aspect category, or sentiment analysis;
- If the study is a survey paper, the results of the study will be identified as a separate study;
- If studies share one topic, the recent one will be selected.

The exclusion criteria are:

- The study is a duplicate based on title;
- The study is not written in English.

2.3 Snowballing

To maximize the completeness of the study to be reviewed, we also implement snowballing technique. The snowballing technique that we used is the backward snowballing by considering all related references in the study contained in the database presented in Table1. This reference was then filtered based on the aforementioned inclusion and exclusion criteria.

3. RESULT AND DISSCUSION

This section explains the process of selecting and filtering studies to produce a fullset of studies to be reviewed. The result of the fullset studies is analyzed based on the year of publication and sub-process of the aspect-based sentiment analysis on the study. Furthermore, the result of the fullset studies is systematically presented using table to answer the research question.

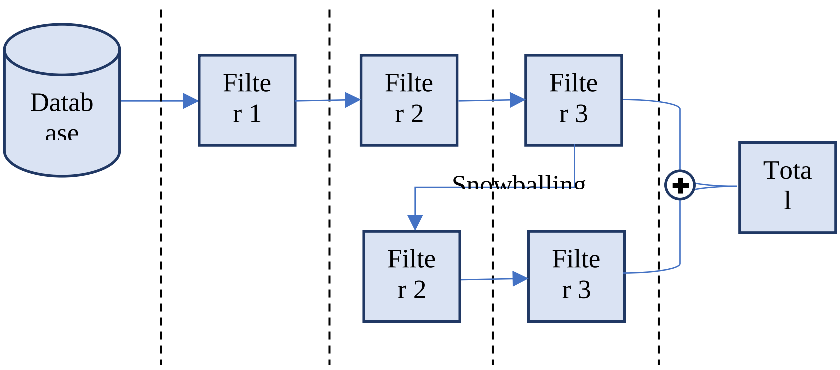

Figure 1. The result of papers at each stage

Figure 1 displays the result of the study selection at each stage. The final result is a merging of the study search in the database using the snowballing process with a total number of34 papers. Fig 2 below is a meta-analysis of the distribution of the publication year of the studies and sub-processes that are the focus of the study.

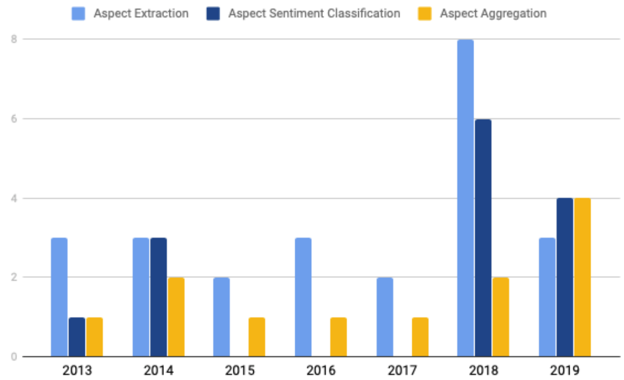

Figure 2. The distribution of studies between 2013 - 2019

In Figure 2, it can be seen that the majority of the studies focuses on the extraction aspect. From 2013 to 2019, there have been many studies on aspect extraction. Most studies were collected from 2018, so the topic of aspect-based sentiment analysis remain attracting among researchers. The final list of studies can be seen in Table 2.

Table 2. Final list of studies

Ref	Author & Year	Title
[8]	Bagheri et al, 2013	Care more about customers Unsupervised domain-independent aspect detection for sentiment analysis of customer reviews
[9]	Xu et al, 2013	Aspect-level opinion mining of online customer reviews
[10]	Hai et al, 2013	Identifying Features in Opinion Mining via Intrinsic and Extrinsic Domain Relevance
[11]	Marrese-Taylor et al, 2014	A novel deterministic approach for aspect-based opinion mining in tourism products reviews
[12]	Zhao et al, 2014	Clustering Product Aspects Using Two Effective Aspect Relations for Opinion Mining
[13]	Quan et al, 2014	Unsupervised product feature extraction for feature-oriented opinion determination
[14]	Zheng et al, 2014	Incorporating appraisal expression patterns into topic modeling for aspect and sentiment word identification
[15]	Maharani et al, 2015	Aspect Extraction in Customer Reviews Using Syntactic Pattern
[16]	Gupta et al, 2015	Summarizing Customer Reviews through Aspects and Contexts

[17]	Xiong et al, 2016	Exploiting flexible-constrained K-means clustering with word embedding for aspect-phrase grouping
[18]	Soundariya et al, 2016	Product Aspect Detection for Sentiment Analysis by Employing Aggrandized Affinity Measure
[19]	Wang et al, 2016	A Unified Framework for Fine-Grained Opinion Mining from Online Reviews
[20]	Kang et al, 2017	RubE: Rule-based methods for extracting product features from online consumer reviews
[21]	Rana et al, 2017	A two-fold rule-based model for aspect extraction
[22]	Shams et al, 2017	Enriched LDA (ELDA): Combination of latent Dirichlet allocation with word co-occurrence analysis for aspect extraction
[23]	García-Pablo et al, 2018	W2VLDA: Almost unsupervised system for Aspect Based Sentiment Analysis
[24]	Wu et al, 2018	A hybrid unsupervised method for aspect term and opinion target extraction
[25]	Dragoni et al, 2018	An unsupervised aspect extraction strategy for monitoring real-time reviews stream
[26]	Pham et al, 2018	Exploiting multiple word embeddings and one-hot character vectors for aspect-based sentiment analysis
[27]	Tran et al, 2018	Estimating Public Opinion in Social Media Content Using Aspect-Based Opinion Mining
[28]	Shafie et al, 2018	Aspect Extraction Performance With POS Tag Pattern of Dependency Relation in Aspect-based Sentiment Analysis
[29]	Marcacini et al, 2018	Cross-domain aspect extraction for sentiment analysis: A transductive learning approach
[30]	Amplayo et al, 2018	Incorporating product description to sentiment topic models for improved aspect-based sentiment analysis
[31]	B. S. Rintyarna et al, 2019	Enhancing the performance of sentiment analysis task on product reviews by handling both local and global context
[32]	A. Firmanto and R. Sarno, 2019	Aspect-Based Sentiment Analysis Using Grammatical Rules, Word Similarity and SentiCircle
[33]	F. Nurifan et al, 2019	Aspect Based Sentiment Analysis for Restaurant Reviews Using Hybrid ELMo-Wikipedia and Hybrid Expanded Opinion Lexicon-SentiCircle

[34]	R. Priyantina and R. Sarno, 2019	Sentiment Analysis of Hotel Reviews Using Latent Dirichlet Allocation, Semantic Similarity and LSTM
[35]	D. Khotimah and R. Sarno, 2019	Sentiment Analysis of Hotel Aspect Using Probabilistic Latent Semantic Analysis, Word Embedding and LSTM

4. CONCLUSION

Research Question: How is the grouping methods in the aspect-based sentiment analysis?

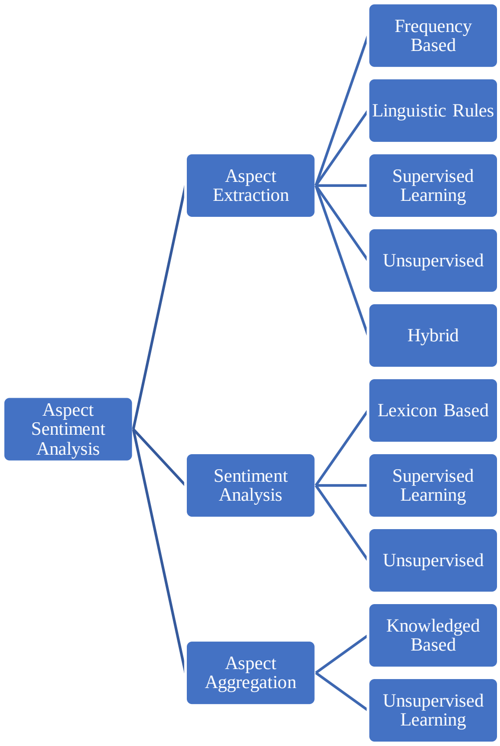

Figure 3. Taxonomy of aspect-based sentiment analysis from full set of studies

This section discusses methods in aspect-based sentiment analysis from a collection of studies in Table 2. For the taxonomic division of the method can be seen in Fig 3. This section explains the sub-process division of the aspect-based sentiment analysis.

a) Aspect Extraction

In the aspect extraction, the methods found in the collection of studies include: frequency based, linguistic rules, supervised learning, unsupervised, and hybrid. All methods discussed in the aspect extraction can be seen in Table 3.

Table 3. Comparison of methods in aspect extraction

Methods	Paperset
Frequency Based	[11]
Linguistic Rules	[8][10][15][16][21][20][25][27][28][32]
SupervisedLearning	[26]
Unsupervised	[13][18][19]

Hybrid	[24]

In-detail explanation of each method is provided below.

b) Frequency Based

Marrese-Taylor et al. [11] use frequency itemset mining to obtain aspects on tourism reviews. First, candidate aspects are collected using POS tagging for all nouns and noun phrases. Then, the frequent itemset mining is used to obtain the aspect mostly used by the reviewers. Frequent itemset mining is based on the algorithm of association rule, where the aspect is frequent if it appears more than 1% (minimum support) on a review. The advantage of frequency based is that this method is simple and easy to implement. The disadvantage of frequency based is that if there is one aspect lacking in frequency, it will be discarded which results in low recall value.

c) Linguistic Rules

This method uses linguistic rules based on POS tagging and dependency relations. Bagheri et al [8] use the POS combination to collect aspect candidates. The aspect candidates are filtered using heuristic rules and modification scores from PMI (Point-wise Mutual Information). In addition, the method also extracts implicit aspects using a co-occurrence graph algorithm from aspects and opinion words. Hai et al. [10] propose methods of collecting aspects by taking intrinsic domain relevance (IDR) and extrinsic domain relevance (EDR) into account. The relevance domain functions as a filtering of candidate aspects in which the process of collecting aspects uses the syntax rules based on POS and dependency relations. The final aspects are obtained once meeting the threshold of IDR and EDR values.

Maharani et al. [15] propose an aspect extraction method on product review from amazon based on the POS pattern of three words in the review. Each word has been predefined its POS tag rules. Aspects that meet the rule will be the final set aspect. Gupta et al. [16] also use self-defined rules based on POS tagging. In contrast to Maharani et al. which use 3 words in collecting aspects, the combination of rules by Gupta et al. uses regular expressions for aspect extraction. Rana et al. [21] collect aspects using POS-based pattern rules. These aspect candidates are then filtered based on frequency filter and similarity pruning. The similarity pruning uses the Normalized Google Distance (NGD) algorithm based on the result of the Google search of two words.

Kang et al. [20] use rules to extract subjective features and objective features. The method to extract the subjective features uses double propagation with the addition of indirect dependencies and comparative construction. Moreover, the method to extract the objective features uses part-whole relations. Dragoni et al. [25] use rules based on dependency relations. The relations used are adjectival modifier, nominal subject, and direct object. Tran et al. [27] collect aspects using the double propagation (DP) method using rules based on dependency relations. The DP method is modified by changing the initial corpus value from a collection of opinion corpus to a collection of aspect corpus.

Shafie et al. [28] also use a combination of rules from POS Tagging and dependency relations and evaluate the most influential combination in collecting aspects correctly. Firmanto et al. [32] compile rules based on constituency parse; they assume the idea that aspect of noun or noun phrase is close to the opinion word. In the process, they break down complex and compound sentences into simple sentences once the closest aspect is extracted if the opinion word is identified.

From the methods above, there are advantages and disadvantages to each method. The advantage of implementing linguistic rules is high precision, since the process of extracting rules is based on grammar and the process does not depend on a particular domain due to the absence of acquiring process. On the other hand, the disadvantage of the method is that if a sentence is grammatically incorrect, it can cause errors in collecting aspect and is highly dependent on the dependency parser of the rule used.

d) Supervised Learning

Pham et al. [26] use a convolutional neural network with 3word embedding features, namely word2vec, glove, and one hot character. The sentence input is entered into the all of the word embeddings. The results obtained from the all of the word embeddings are entered into the CNN channel of which result is called multiple sentence representation. These three sentence representations are combined and incorporated into the non-linear activation function to produce global sentence representation. Ultimately, the global sentence representation is used as an input for a single neural network using the softmax function to produce aspect category vector for aspect prediction. The supervised method produces the best performance based on training data; Having correct training data, this method has the best performance value; this method is, however, highly dependent on the domain used. Data with restaurant domain will have different performance result when used in the e-commerce domain. It means that this method lacks in the process of finding the correct data as well as the labeling and annotation process.

e) Unsupervised

This method does not use labelled data as in the supervised learning. Generally,this method is based on distance similarity and word frequency distribution. Distance similarity method measures the closeness of the aspect word to the seed aspect. Whereas, the word frequency distribution is based on the word probability of the static method; in general, the existing method is the development of the LDA (Latent Dirichlet Allocation) method.

Quan et al. [13] extract aspects by calculating the association between aspects and domains. The similarity method used is a combination of Pointwise Mutual Information (PMI) and Term Frequency-Inverse Document Frequency (TF-IDF). The final set of the aspects, if it meets the criteria in noun form, will have its similarity value exceeding a threshold with the corpus domain. Soundariya et al. [18] propose a method of extracting aspects by calculating the similarity of aspects with seed aspects, called affinity measure. Aspect candidates are obtained by dependency analysis for single word aspects, and by frequency and length-based aspect relation method for multi word aspects. This method filters aspects based on frequency in the corpus alongside the length of the word combination. It uses threshold to extract multi-word aspects. Once the aspect candidates are obtained, pruning is done to remove the redundant aspect, and calculate the value of affinity measure. The final set of the aspects is the result of affinity measure extended using lexicon synonym. Wang et al. [19] modify the double propagation method for the aspect extraction at each iteration using Opinion Relation Graph (ORG). ORG aims to remove false result on opinion candidates, aspect candidates, and syntactic pattern candidates.

Xu et al. [8] conduct aspect extraction based on LDA by limiting each sentence to one topic. From the LDA process, there are two indicators to determine the subjectivity and objectivity of an aspect and indicator to determine sentiment. Zheng et al. [13] extract aspects by adding an Appraisal Expression Pattern (AEP) to the LDA. The Appraisal Expression Pattern uses POS and dependency relation to determine aspects and opinions. Shams et al. [21] modify the LDA by adding co-occurrence relationship as initial knowledge. Co-occurrence functions to filter the result of LDA to improve the quality of the aspect extraction.

The unsupervised method does not require a training process, so labeling the dataset is not required. This method is highly dependent on the initial seed in the form of a guided word to obtain good accuracy; Then the distance or topic modeling method used to the seed word to determine its aspect.

f) Hybrid

Hybrid method is a combination of several existing methods. Generally, this method combines linguistic rules with other methods. Wu et al. [24] extract aspects by combining deep learning with linguistic rules. Aspect candidates are obtained from linguistic rules,filtered the correlation domain using word embedding and cosine similarity. The filter result become training data from deep learning. For data labeling, the filter result is automatically labeled using sequence labeling with BIO format (Beginning, Inside, Outside).

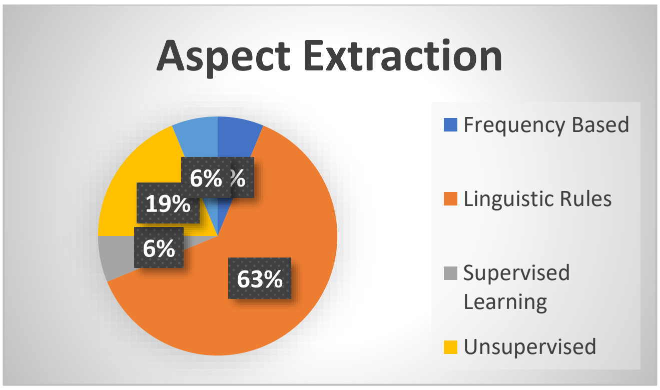

Fig. 4. The mostly used methods in aspect extraction

In Figure 4, the linguistic rules and unsupervised methods are widely used for the aspect extraction because those methods do not require data labeling. The linguistic rules have the advantage of aspect extraction from word structure thus the high accuracy in grammatically correct sentences. However, this method has disadvantage of having to manually define patterns and not being applicable to grammatically incorrect sentences. The unsupervised method generally uses the distance similarity with the seed word; the process of selecting the correct word will produce high accuracy. The overall advantages of the methods used in the previous study can be seen in Table 4; while, the overall disadvantages can be seen in Table 5.

Table 4. The advantages of the methods used in aspect extraction

Advantage	Method
Easy to use	Frequency based
No data labeling needed	Frequency based, linguistic rules, unsupervised
Sentence representation by considering context	Supervised learning
Pruning process to filter out irrelevant aspects	Linguistic rules
Determining subjective and objective sentence	Linguistic rules

Table 5. The disadvantages of the methods used in aspect extraction

Disadvantages	Method
Unable to process word in low frequency sentence	Frequency based
Dependent on parsing method in generating rules	Linguistic rules
Unable to process grammatically incorrect sentences	Linguistic rules
Data labeling required	Supervised Learning
Highly dependent on seed word as guided on aspect	Unsupervised

g) Sentiment Analysis

In the previous studies, the sentiment analyses used are lexicon based, supervised learning and semantic based. The comparative detail can be seen in Table 6.

Table 6. Method comparison in sentiment analysis

Method	Paperset
Lexicon Based	[9][11][13][23][25]
Supervised Learning	[26][34][35]
Semantic Based	[27][31][32][33]

In-detail explanation of each method is provided below.

h) Lexicon Based

Dragoni et al. [25] use SenticNet, General Inquirer vocabulary, and MPQA dictionary by adding up all the polarity values of the three. Marrese-Taylor et al. [11] use 3 rules, namely word rules (in the form of positive/negative word value), negation rules (if there is negation), and intensify rules (if there is a word which emphasizes). Quan et al. [13] extract feature-opinion pair using typed dependency and the General Inquirer to determine the sentiment of the feature-opinion pair. Xu et al. [9] determine the sentiment polarity value of a sentence using the polarity value from MPQA and SentiWordNet. García-Pablo et al. [23] determine lexicon sentiment using positive and negative seed word for each aspect.

This method has the disadvantage of the polarity value of a static word. In certain cases, one word can have two polarity values; for example, the word "long" in the aspect of battery life is positive, but in the aspect of performance is negative. The advantage of lexicon based is that it is easy to implement.

1) Supervised Learning

Pham et al. [26] use a convolutional neural network with training data from sentences which had been labeled in terms of sentiment. Reza et al. [34] and Dewi et al. [35] use the LSTM method in determining sentiment. The feature used is word embedding using glove.

The supervised learning method requires data that are manually labeled by one or more linguists so that the accuracy is largely determined by the quality of the test data.

2) Semantic Based

Tran et al. [27] use the word tuple synonym from Wordnet to determine the polarity value of the sentiment by calculating the average polarity values of all the synonyms. This method is also developed to be able to recognize sentiment based on context. B. S. Rintyarna et al. [31], A. Firmanto et al. [32], and F. Nurifan et al. [33] use SentiCircle [36] to determine the sentiment based on the semantic proximity to other words of the same context. Prior to the sentiment determination process, sentence grouping based on context is carried out in their respective studies, so the word sentiment in the same context will have the same sentiment value.

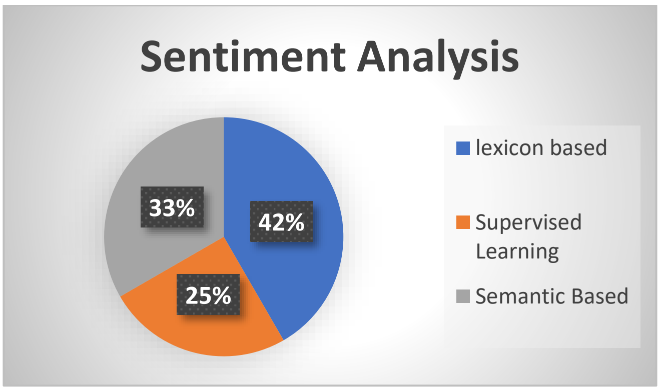

Fig. 5. The mostly used methods in sentiment analysis

In Fig 5, Lexicon based is the mostly used method. The overall advantages and disadvantages from the previous studies can be seen in Table 7 and 8, respectively.

Table 7. The advantages of the methods used in sentiment analysis

Advantage	Method
Easy to use due to the availability of lexicon dataset	Lexicon based
Determining sentiment based on context	Semantic Based

Table 8. The disadvantages of the methods used in sentiment analysis

Disadvantage	Method
Annotation on training data required	Supervised Learning
Sentiment is static based on context	Lexicon Based
Data grouping based on context required	Semantic Based
Dependent on data domain	Supervised Learning

A. Aspect Aggregation

In terms of aspect aggregation, the methods used are distance based, knowledge based, and unsupervised learning. The comparative detail can be seen in Table 9.

Table 9. Method comparison in aspect aggregation

Method	Paperset
Distance Based	[16][22][27][32][33]
KnowledgeBased	[10][17][19][34][35]
Unsupervised Learning	[12]

In-detail explanation of each method is provided below.

1) Distance Based

Shams et al. [22] determine the similarity of two aspects using Hub set and word relations. Hub set is 2 hub words, in which hub words are words that are strongly related to aspects. The strength of the relation is determined based on the total number of aspects and length of the document. Tran et al. [27] use the Synset of Wordnet to determine the similarity of word aspects. Gupta et al. [16] determine aspect similarity by combining Jaccard similarity, Point wise Mutual Information (PMI), and WordNet.

A. Firmanto et al. [32] group aspects into categories using distance cosine similarity, in which the aspects are grouped based on keywords obtained from Wikipedia. Each category has keywords obtained from the Wikipedia page. Fast Text [37] word embedding is used as a vector in calculating cosine similarity. F. Nurifan et al. [33] use the cosine similarity method combined with Elmo [38] as word embedding. In the process of combining aspects, the keywords are obtained from Wikipedia. The difference from the previous process is that the embedding calculation of the keywords use the average of Elmo value of which distance calculated by the Elmo word embedding from the aspect word in the sentence.

2) Knowledge Based

Knowledge similarity aims to look for semantic similarity among words. The use of knowledge based is generally in the form of dictionary or other external resources. Wordnet is one of the common dictionaries used in study. Similarity in Wordnet is based on the distance between a node and other nodes in a tree structure. [17], [10] and [19] use Wordnet similarity alongside other similarity measures in the merging of aspects. Xiong et al. [17] use cosine similarity and Wordnet similarity, a combination based on a weight that can be set and used to determine the strong attachment of words in which the word should be in a group or cluster. Hai et al. [10] use Jiang-Conrath Similarity to group the aspect. Wang et al. [19] use Wordnet similarity to look for semantics among words. R. Priyantina [34] and D. Khotimah [35] use the Wordnet similarity method of the Wu-Palmer method in classifying aspects of sentences with the seed word. Seed words represent categories that are used and selected manually.

3) Unsupervised Learning

Zhao et al. [12] use hierarchical clustering based on the distance from the literal aspect, relevant aspect and irrelevant aspect for aspect aggregation. Literal aspect is the similarity among words based on dictionary and similarity method. Relevant aspect is a word that has a suffix relation in a sentence. Irrelevant aspect is the opposite of the Relevant aspect.

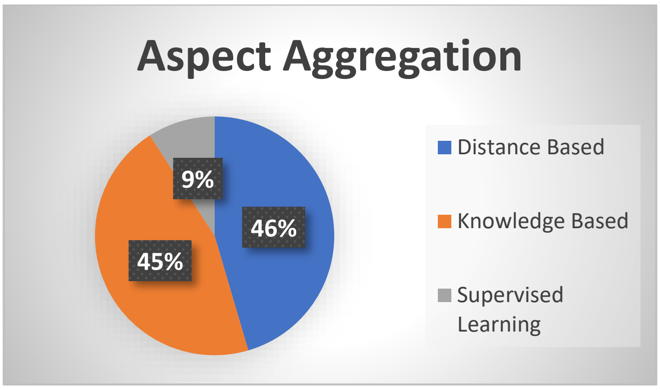

Fig. 6. The mostly used methods in aspect aggregation

The methods used for aspect aggregation generally have the similarity of using distance or in the grouping process. In Figure 6, the distance method is the most widely used in study. This method generally requires keywords or initial words of which distance to be calculated with the aspect words in the categorization process. The overall advantages and disadvantages in previous studies can be seen in Table 10 and Table 11.

Table 10. The advantages of the methods used in aspect aggregation

Advantage	Method
Use of knowledge to increase accuracy	Knowledge Based
No data labeling required	Distance based, knowledge based, unsupervised learning

Table 11. The disadvantages of the methods used in aspect aggregation

Disadvantage	Method

Determining initial seed word	Distance based, knowledge based, unsupervised learning
Not using concept in finding keywords	Distance based, knowledge based, unsupervised learning
Calculation using 2 words, not multiword among phrases	Distance based, knowledge based, unsupervised learning

I. Conclusion

This study summarizes the various methods used for aspect-based sentiment analysis. There are three stages in the aspect-based sentiment analysis, namely: aspect extraction; sentiment analysis; and aspect aggregation. For aspect extraction, the most widely used method is Linguistic Rules. This method formulates rules based on the parser or part of speech of a word in the process of extracting an aspect. This method depends on the accuracy of the parser used, and is generally prone to not handling non-standard sentence. For sentiment analysis, the most widely used method is Lexicon Based. This method requires a lexicon opinion, which is generally available, such as SentiWordnet. In this method, the process of determining sentiment is not based on the sentence context. For aspect aggregation, the most widely used method is Distance Based; this method measures the distance between two words where the word is derived from the initial seed word which is a keyword with the aspect word in a sentence.

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