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Aspect-Opinion Extraction with Polarity Estimation through Dependency Relation Analysis

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Abstract: Opinion Mining (OM) or Sentiment Analysis (SA) emphasizes on the study of the customer's behavior likewise; as attitude, requirements, and desires about a product or service. Aspect-based Sentiment Analysis (AbSA) provides an analysis of customers' sentiments on different product/service aspects or features at a finer level, in the form of reviews posted on social media platforms. In AbSA, the core task is to identify and extract product facets, ranking, and then classification. For this purpose, supervised, unsupervised, and semi-supervised methods are used for Aspect Extraction (AE). Moreover, several approaches and algorithms have been recommended in the literature. Dependency Relation Analysis (DRA), an AE method; uses Type Dependency Relations (TDRs) to extract significant product aspects linked with sentiments. For example, linguistic features serve as a mainstream backbone for language analysis. This study intends to extract aspect-opinion pairs along with their sentiments, applying an unsupervised approach by using DRs' and rule-based algorithms. To evaluate the proposed system's effectiveness, the APR dataset was used and results were compared with the baseline studies. The outcome from the proposed method demonstrates that it outperforms the baseline studies with 0.85, 0.75, and 0.79% for Precision, Recall, and F1-measure performance metrics, respectively. Besides it, the customer reviews polarity estimation was investigated at a large scale with an enhanced rule-based algorithm that results in improved effectiveness.

Keywords: k Customer's behavior, aspect extraction, sentiment analysis, polarity estimation, text mining, opinion mining.

1. Introduction

Data Mining (DM) is a captivating area of CS that is proclaimed with the knowledge discovery in databases to predict future trends. To investigate, model analytically, and then classify utilizing structured or semi-structured textual data, text mining combines conventional DM and text analytics approaches [1]. Sentiment analysis is the flashpoint arena of Text mining. Some of the various sub-tasks that are performed in sentiment analysis include polarity estimation (PE), opinion summarization (OS), document summarization (DS), text summarization (TS), irony detection (ID), spam detection (SD), intention mining (IM), named entity recognition (NER), emotion and smiley's analysis (ESA), and subjectivity detection (SbD) [2]. Sentiment analysis can be done independently at the level of the document, paragraph, sentence, aspect, concept, and lexicon [3]. The polarity of distinct aspects of the product is discovered at the pulverized level by the aspect-level analysis of sentiment orientation [4].

In AbSA, reviews are used as feedback by companies to improve and provide better services, enhance their product quality, compete with their counterparts and industry, to provide personal and more responsible services to their valued customers. Different methods which comprise Supervised, Unsupervised, and semi-supervised are used and discussed by many research studies to recognize and excerpt aspects/features from product reviews. In this study, we have focused our attention on only Unsupervised methods for aspect extraction using DRA's. The Unsupervised AE methods reduce the burden of training the data, as done by the supervised methods.

Online users can now express their ideas, feelings, and opinions regarding a variety of topics, including products, services, politics, healthcare, education, and more thanks to the quick development of social media platforms [5]. Prior to the flourishing development of the internet community, when a person needed to make a decision about whether or not to purchase a good or service, he or she typically sought advice from friends, experts in the field, or members of their family, or relied on paid commercial advertisements produced by the product producer. Similarly, to this, organizations who want to hear from their customers about their goods and services perform surveys, focus groups, and opinion polls, or they contract third parties to do so. With the introduction of Web 2.0, it became a reality that opinions and information shared by individuals across the globe regarding specific entities, encompassing a range of goods, problems, policies, and services, were now easily accessible. Due to the massive and unprecedented use of social media platforms, customers are now more likely to base their purchasing decisions on the reviews found there [6].

The goal of Aspect-based Opinion Mining (OM) or AbSA is to find aspects and the sentiments associated with each aspect that has been stated in online evaluations. The earlier research on aspect-based OM attempts to extract aspects and the associated feelings [4, 7, 8]. The basic tasks of aspect-based OM can be decomposed into (i) extraction of aspect terms, (ii) extraction of sentiment expressed towards the extracted aspects, (iii) clustering or grouping of similar aspects, (iv) determining the polarity of opinion-bearing terms, and (v) aspect-based summary generation depicting the aspects, sentiments along with its polarity orientation [9].

Another family of grammar on the list, known as dependency grammar, is significant in today's speech and language processing systems. Phrasal elements and rules governing phrase structure are not directly involved in these formalisms. The syntactic structure of a sentence is instead described by the words (or lemmas) in a phrase and a corresponding set of directed binary grammatical relations that hold among the words [10]. The dependency-parsing community's standard graphical method is used to show a dependency-style analysis in the diagram that follows [11].

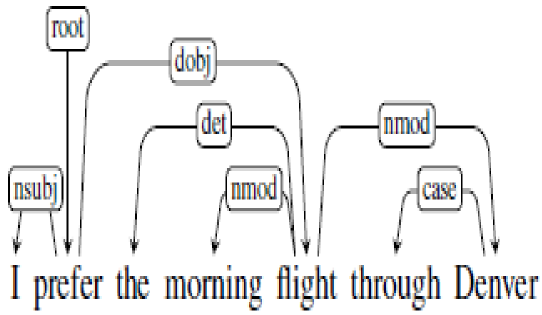

Figure 1. Linguistic analysis of text using Dependency relation analysis

The primary concentration of the proposed research study is based on the extraction of aspects, categorizing aspect associated sentiments, and generation of an aspect-level abstractive summary that depicts and attends to the major aspects identified in the previous step. The aspect-level abstractive summary is not included in this study and is left to our future work. The earlier aspect-based OM studies [10], [12], and [13] served as the inspiration for the current work. The earlier discussed studies cast off a limited set of dependency relations, which did not cover all the linguistic patterns, and utilized a limited set of rule-based patterns for the purpose of aspect extraction, which overlook and miss some of the important aspects bearing terms with its associated sentiments. As a result, this research study suggests an integrated and hybrid model encompassing an extended set of TDRs as a linguistic pattern used in DRA's, an extended set of rule-based patterns to include all the language phonemes to broaden the coverage, and a sentiment classification module. The outcome from the AE process in the form of aspects with their opinions contribute to different domains in text processing, to name a few, like Automatic Summary Generation involving both extractive and abstractive versions, Recommender Systems, and Review Summarization [14].

Aspect-based OM becomes a challenging activity under the umbrella of sentiment analysis, due to the different factors like unstructured nature and behavior of the reviews, the freestyle writing (includes slang words e.g., XOXO for deep friendship, acronyms F9 used for fine) of the online users. These online reviews serve a multipurpose job, on one hand, it facilitates and eases the decision making, reduce the time to read all reviews to reach a final decision, on the other hand, these reviews act as feedback, it permits businesses to improve and update their goods and services.

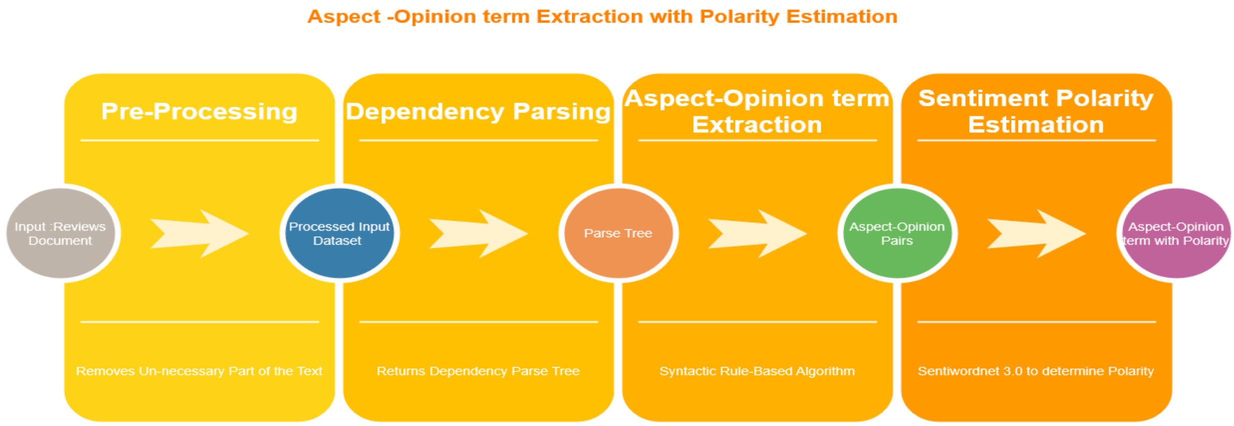

Figure 2. Aspect-Opinion term Extraction with Polarity Estimation

The Aspect and Opinion (targets) extraction from customer reviews is a two-step process that is interconnected. Before using the dependency relation rules, First, the authors looked into a few principles based on observations and a few guidelines and rules from past research by other academicians [12],[15]. Then the proposed study expanded these rules to incorporate new linguistic elements that were not covered by earlier studies. So, in the first step, the proposed study extracted the Aspect-Opinion (AO) pairs using an extended set of Dependency relations and in the next, estimated the polarity of extracted opinions using Sentiwordnet lexicon to determine the sentiment of online users.

The following are the study's main contributions:

- Developed an algorithm for aspect-sentiment extraction and proposed an enhanced set of Type Dependency Relations (TDRs) and criteria for accurately extracting aspects and their associated sentiments.
- Using lexicon-based classification approaches, the authors suggested a sentiment classification strategy for categorizing aspect-related sentiments.

Following are the plans for the remaining portions of this paper. Section 2 is dedicated to introducing related works on aspect extraction and aspect-opinion extraction of this article. Section 3 presents a detailed description of the proposed methodology for Aspect-Opinion Pair extraction with sentiment prediction. Section 4 demonstrates the experiment settings, Section 5 is dedicated to presenting the study outcomes and finally, Section 6 concludes the research study with its outcomes, limitations, and future endeavors.

2. Related Work

The authors [16] devised a rule-based approach that aims to utilize dependency relations and decision tree classifiers to extract features from reviews. SentiWordNet is ultimately applied to estimate the polarity of the extracted features. The dataset evaluation metrics are precision, recall, and F-measure, which consist of an iPhone and a digital camera. Rule 1,2, and Rule 1,2,3 and 4 are used in empirical evaluation to extract the feature and its associated Sentiments; the latter delivers the best outcomes. There hasn't been any comparison to previous studies.

It was covered in [17] how explicit aspect extraction from customer reviews of various electrical products utilizing syntactic patterns. The noun, adjectives, adverbs, and verbs are the four syntactic types. On five different products, data was gathered from Amazon.com and epinion.com. In comparison to the Bing Liu research study, the empirical outcome shows a 0.5% improvement in recall, 0.3% improvement in precision, and 0.6% decline in F-measure.

In this study, the idea of using graph theory concepts for feature extraction is pursued. Using domain dependency graphs technique for the topic-specific domain was put out by the author [18] as a means of identifying and extracting various characteristics from product reviews gathered from Amazon. The text is first pre-processed, and then the LDA algorithm is used to choose the topics. The associated phrases are then estimated using a probabilistic topic distribution. To identify POS tags, dependency parsing is used, and dependency parsing offers language analysis. A DDG is finally created for topic-specific terms. The retrieved aspects from the graph are weighed using the TF/IDF technique. The results of a tiny dataset are taken into account, and they are contrasted to those of a Frequency-based technique, demonstrating how well the suggested method extracts topic-specific features from product reviews.

To replace the preceding manual rule selection and aspect extraction approaches, the authors of this work [19] presented an automatic rule selection method. There are three proposed rules for extracting aspects: R1 (opinion words), R2(aspects), and R3 (extract new words). These rules use aspects and opinions to extract new words (R3) utilizing double propagation. Accurate aspects can be derived by using automatic criteria since Double Propagation generates redundant and noisy aspects. The Bing Liu data set and a self-made dataset is used to extract aspects. The empirical study's results demonstrate an improvement in the metrics for information retrieval.

To preserve the most crucial aspects of a product, this study addresses frequent feature mining, a well-known DM idea. An algorithm based on rules was suggested by the author of this study [12] for the extraction of product attributes. Before applying Rules from a given set to choose aspects, Dependency Relation Analysis is used to find syntactic patterns. The most frequent features are chosen as candidate aspects using the Apriori method. The product reviews dataset was obtained from Amazon, and the outcomes reveal improvements of 12% in precision, 14% in recall, and 18% in F-measure when compared to baseline techniques.

This work extends the notion that a noun is a crucial identifier of a feature and an adjective is a crucial choice for aspect terms that express an opinion to other language terms alike subjects and verb predicates. this research uses the dependency relation analysis to offer an expanded feature extraction approach based on the links between "Verb-Object, Subject-Predicates and Attributes". The extended table list also contains a list of emoticons. While comparing the outcomes of the KNN method under various feature vector space with Information Gain, Mutual Information, the proposed Extended Dependency Grammar established a favorable result with its benchmark studies. In future work, deep learning is suggested [15].

The author of this work proposes a hybrid approach to aspect extraction, in which aspects are first extracted through dependency relations, followed by further aspect pruning using a frequency-based method to remove any extraneous aspect extraction coverage, and finally, sentiment classification using Sentiwordnet. [20].

Many studies exclude bigram phrases like (battery life, touch screen). In this work, these multiword issues are addressed. The authors extracted numerous aspects with multiple feelings using dependency relations analysis and POS tagging. With the aid of POS tagging, the author of this study selects eight dependency relations to identify and extract multiword aspects as well as a variety of emotions. While using datasets from the laptop and restaurant industries, the outcome demonstrates improvement in IR metrics [21].

In this research study, the author utilizes CNN approach for aspect extraction. The author augmented conventional CNN with non-static CNN, multi-kernel convolution layer and dropout regularization. Skip-gram trained word2vec model is used as an embedding method for feature extraction. The proposed model was evaluated on the SemEval-2016 task on the restaurant and laptop domain. The proposed model gets a 0.75% F1 score on the restaurant and a 0.51% F1 score on the laptop domain [27].

A deep learning approach is employed in this research study to extract opinion targets from the movie reviews posted online. The bi-LSTM model is employed for the feature extraction task, a Chinese movie review corpus is engaged for evaluation. A visual display is used for the scoring function. In the future the author intends to extend the research work by identification of the emotional sentences and using an app for the visual display of the sentiments with score [28].

In this paper [29], the author suggests two methods for aspect extraction. SemEval, yelp, and Kaggle datasets are used for the extraction purpose. A multivariate filter-based approach is suggested as the first technique for feature extraction, in the second technique a dependency parsing method is applied. The second technique performs better in comparison to the first technique. At the next level, a hybrid method encompassing the both above-discussed methods for feature extraction were applied on the selected datasets and got an improvement in accuracy and F-1 score.

Customer online reviews (COR) play a vital role in the product acceptance or dissatisfaction levels. The proposed research study implements intelligent rules with machine learning model. The extracted specific aspect polarity is determined by using the Naïve bayes classifier. The real opinion of the online customer is distinguished by some intelligent rules based on the hypothesis [30].

Table 1. Related Work on Aspects Extraction through Dependency Relation Analysis

Paper title	Objective	Methodology	Findings	Limitations
[16]	Explicit feature extraction	Decision Tree classifier, dependency parser, WEKA	Improve recall for IR	-Did not cover fuzzy terms,
[17]	Explicit aspect extraction	Using syntactic patterns aspect extraction is performed	Improvement in IR matrices with comparison to the Bing Liu dataset	-Implicit aspect extraction is not considered.

				-Sentiment Polarity is not determined
[18]	Topic Modeling and Aspect Identification	-Use LDA for topic modeling -Applied Domain Dependency Graph (DDG) for Aspect identification - Use TF/IDF for filtering	-Aspects identification through specific topics. -Precision up to 63%	-Only use Noun and adjectival modifier relations for aspect identification.
[19]	Aspect extraction	-Using dependency relations analysis to extract aspects. -Automatic rule selection for accurate aspects extraction	-Improvement in IR metrics with comparison to CRF and DP algorithms	-To employ other semantic rules. -To use other rule selection algorithms like simulated annealing or genetic algorithms
[12]	Aspect extraction	-POS tagging -Dependency relations analysis -Apriori algorithm for frequent feature mining	-Improvement in the precision, recall, and f-measure with an increase of 20%, 16%, and 10% respectively in comparison to state-of-the-art systems.	-Use of a Limited number of Dependency Relations for aspects extraction. -Sentiment Polarity is not determined.
[15]	Aspect extraction	Dependency grammar analysis KNN algorithm	Improvement in Precision and Recall with comparison to IG, MI.	-Only consider Verbs as the main relation for feature extraction.
[20]	Explicit aspects extraction	Dependency relations analysis Frequency-based pruning	Improvement in IR metrics while comparison with	-Implicit aspect extraction is not covered.

			other competitive systems	
[21]	Explicit aspect extraction	Using POS and Dependency relations to extract multiple aspects with multiple sentiments	Improvement in IR metrics	-Only explicit aspect extraction performed –Sentiment orientation is not performed.

3. Proposed Methodology

The diagram below displays the workflow model for sentiment polarity estimation along with AO-Pair term extraction. Detail of each processing step is given below.

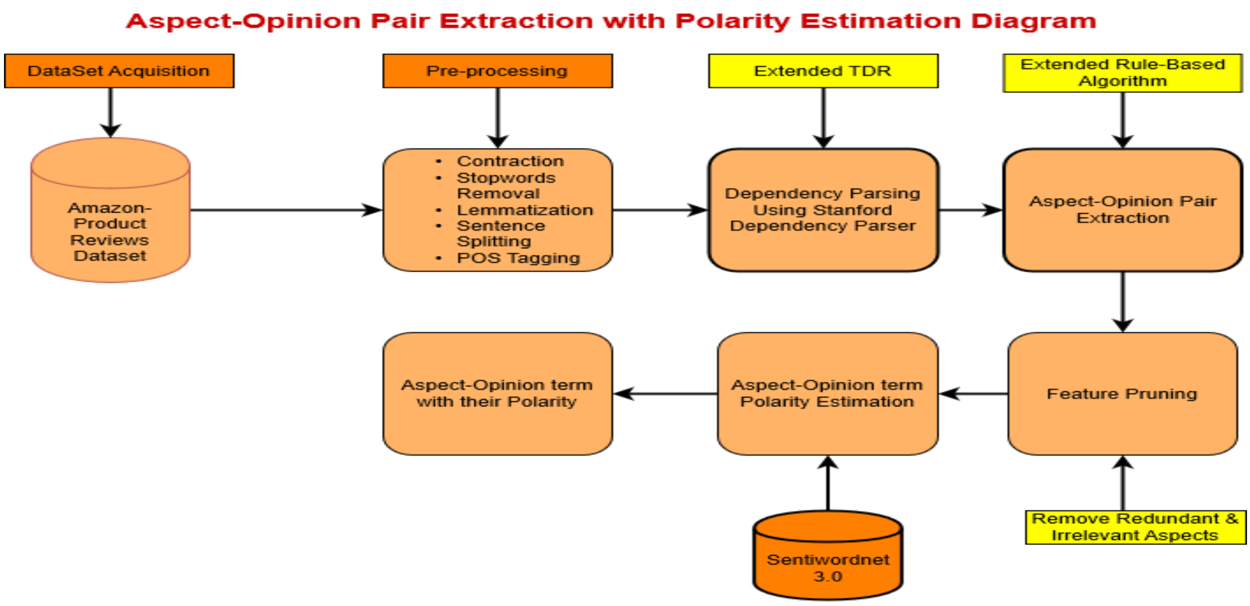

Figure 3. Aspect-Opinion term Extraction with Polarity Estimation Diagram

3.1 Dataset Acquisition

This research study acquired a publicly available benchmark Amazon Product Reviews Dataset, on two domains: Electronics and Fine Food. This dataset has a huge repository of approximately 82.83 million unique reviews on different products, aggregated from 20 million web users, with a timespan from ranges from 1996 to 2016. Whereas each review consists of 140-160 characters.

3.2 Data Pre-processing

- Contractions Removal: The Human usually opts for shorthand linguistic notations for speaking and writing utterances, but for computer to understand these symbolic notations, these will be converted into their normal forms. For example, "couldn't've" will be converted to "could not have".
- Data Cleaning: In this step, we apply, data cleaning which will remove unnecessary characters and symbols (#, &, },), :, URL's" using regular expression.
- Stopwords Removal and Lemmatization: In this step we apply, Stopwords removal, depletion to lowercase, and lemmatization will be performed to convert the inflected words to their basic word form.

- Sentence Splitting and Tokenization: In this step sentence splitting and Part of speech (POS) tagging will be performed.

3.3 Dependency Parsing

After data pre-processing the next step is to run Stanford Dependency Parser[1], to extract type dependency relations (TDRs). TDR returns triplets in the form, "Relation-name, (governor- dependent)", the name of the dependency relation, and a dependency association amongst the determinant i.e., governor to its dependent.

[('ROOT', 0, 2), ('nsubj', 2, 1), ('compound', 4, 3), ('dobj', 2, 4), ('amod', 4, 5), ('acl', 5, 6), ('nummod', 10, 7), ('advmod', 10, 8), ('advmod', 10, 9), ('nmod:tmod', 11, 10), ('ccomp', 6, 11), ('nummod', 13, 12), ('nmod:npmod', 14, 13), ('amod', 15, 14), ('dobj', 11, 15)].

3.4 Aspect-Opinion (AO)- Pair term Extraction

In this step, AO-pairs terms will be extracted using an extended rule-based algorithm. The proposed study uses an extended set of TDRs, which consists of 7 dependency relations with the inclusion of new POS patterns with Nsubj3, Dobj1, and Amod3 by considering "Verb" as opinions (targets) to cover all possible linguistic terms. An expanded TDR list is utilized in Table 2: 1) introducing Nsubj3, Amod3, and Dobj1 to consider the verb as an opinion and the noun as an aspect to extract AO-pairs, for example, "Hammad Likes the new iPhone Pro-Max" where in the sentence Like represents the verb, which expresses a favorable intention or feeling of the consumer about object iPhone, which is a noun and will be extracted as an aspect. 2) Advcl relation: this relationship explains: the adjective signifies the sentimental term and the noun embodies the aspect term. 3) Compound: Compound relation elaborates that, authors have focused on aspects with multiple words, such as battery life. In the previous studies the composite noun is somehow overlooked. So, to extract multi-word nouns compound clause is considered in this study. In the Compound relation, the first token represents the first part of a composite noun, while the second token represents the second part of the composite noun, and they will be combined to represent a multi-word noun. For example, If the TDR is "nsubj1" and the first token is "Noun" and the second token is "Adjective", then the first token will be extracted as an aspect, and the second token will be extracted as an Opinion word. Similarly, all the customer reviews will be parsed through these TDRs to extract AO-pairs terms. The detail of these TDRs is given in Table-2.

Table 2. AO-Pair Extraction using Extended TDR

S. No	Tdr	Pos Tag Pattern	Result	Example
1	Nsubj1	W1: (NN/NNS/NNP) && W2: (JJ/JJR/JJS)	W1: Aspect, W2: Opinion	Phone Good
	Nsubj2	W1: (JJ/JJR/JJS) && W2: (NN/NNS/NNP)	W1: Opinion, W2: Aspect	Great Display
	Nsubj3	**W1: (VB/VBD/VBG/VBN/VBP/VBZ) && W2: (NN/NNS/NNP)**	**W1: Opinion, W2: Aspect**	**Drains Internet**

[1] https://nlp.stanford.edu/software/lex-parser.shtml

2	Amod1	W1: (NN/NNS/NNP) && W2: (JJ/JJR/JJS)	W1: Aspect, W2: Opinion	Phone Smart
	Amod2	W1: (JJ/JJR/JJS) && W2: (NN/NNS/NNP)	W1: Opinion, W2: Aspect	Specially Screen
	Amod3	**W1: (VB/VBD/VBG/VBN/VBP/VBZ) && W2: (NN/NNS/NNP)**	**W1: Opinion, W2: Aspect**	**Big Deal**
3	Dobj1	**W1: (VB/VBD/VBG/VBN/VBP/VBZ) && W2: (NN/NNS/NNP)**	**W1: Opinion, W2: Aspect**	**Talking S6**
	Dobj2	W1: (NN/NNS/NNP) && W2: (JJ/JJR/JJS)	W1: Aspect, W2: Opinion	Screen Good
4	Nmod: npmod 1	W1: (NN/NNS/NNP) && W2: (JJ/JJR/JJS)	W1: Aspect, W2: Opinion	Phone Good
	Nmod: npmod 2	W1: (JJ/JJR/JJS) && W2: (NN/NNS/NNP)	W1: Opinion, W2: Aspect	Bad Display
5	**Advcl**	**W1: (NN/NNS/NNP) && W2: (JJ/JJR/JJS)**	**W1: Aspect, W2: Opinion**	**Smart Phone**
6	Xcomp	W1: (NN/NNS/NNP) && W2: (JJ/JJR/JJS)	W1: Aspect, W2: Opinion	Protector Great
7	**Com-pound**	**W1: (NN/NNS/NNP) && && W2: (NN/NNS/NNP)**	**W1: Aspect, W2: Aspect**	**Battery Timing**

3.5 Filter Pruning

The AO-pair extraction process usually returns some redundant and irrelevant AO pairs, so pruning is required to get accurate AO pairs. In the Filter pruning step, a double check on the AO-pair extraction process is performed. During the AO-extraction process, first, it is observed whether the extracted opinion has its entry in the Sentiwordnet lexicon, then it is extracted, otherwise its entry is rejected. Similarly, the extracted aspect is also pruned through a Product List (PL) table. The PL table contains information about Product names, technical terms, and general terms. So, if the extracted aspect entry does not exist in the PL table, it should be dropped from the extracted aspect list.

3.6 Polarity Estimation

In demand to establish the polarity of the extracted AO-Pair terms, SentiWordNet 3.0 [22] is used. The sentiment orientation of the retrieved AO-pair terms is determined using three polarities: positive, negative, and neutral.

4. Experiments

4.1 Experimental Settings

4.1.1 Datasets

On datasets including product reviews, experiments are conducted to gauge the effectiveness of the suggested approach. The proposed study evaluates the model performance on the Amazon reviews dataset acquired from Stanford Network Analysis Project (SNAP) [23], among the available list of reviews on different products and items two domains are selected to conduct experiments, which are the Cell Phones and Accessories dataset and Amazon fine food reviews dataset, available online at, http://snap.stanford.edu/data/amazon/productGraph/categoryFiles/reviews_Cell_Phones_and_Accessories_5.json.gz and https://www.kaggle.com/snap/amazon-fine-food-reviews. The Amazon fine food database contains 568,343 customer reviews, whereas the Amazon Cell Phone database contains 82,815 customer reviews. This study selects the 20,000 reviews at random from both data sources for the experiment.

4.1.2 Pre-Processing Details

For both domains, the authors filter out user reviews that are too short/long and restricted the user review size between 140-160 characters. For the implementation purpose, Anaconda Spyder 5.0 environment, Stanford Dependency Parser 3.91, and Python Language are used.

4.2 Evaluation Metrics

Following many previous studies on aspect-opinion extraction and information retrieval, this study chooses Precision, Recall, F-measure, and accuracy [24] to automatically quantify how well a model fits the data. To experiment, a collection of review documents, each containing several different product aspects with their opinions are selected, and three evaluation performance measures: Precision, Recall, and F1-measure are opted to determine the relevance of extracted aspects terms with their opinions. The confusion matrix is used to construct these evaluation metrics, as illustrated in Table 3.

Table 3. Confusion Matrix

Predicted Value	**Actual Value**	
	Positive	Negative
Positive	True Positive (TP)	False Negative (FN)
Negative	False Positive (FP)	True Negative (TN)

4.2.1 Precision, Recall, and F1-measure

Recall is the percentage of relevant documents that have not been recovered, whereas precision is the percentage of relevant documents that have been retrieved in response to the topic [25].

The definitions of the precision and recall measures are:

Precision = Number of documents that are relevant / Number of retrieved documents

$$Precision = \frac{TP}{TP+FP} \tag{1}$$

$$Precision = \frac{Extracted\_Aspect \cap True\_Aspect}{Extracted\_Aspect} \tag{2}$$

Recall = Number of retrieved documents that are relevant / Number of relevant resources

$$Recall = \frac{TP}{TP+FN} \tag{3}$$

or

$$Recall = \frac{Extracted\_Aspect \cap True\_Aspect}{True\_Aspect} \quad (4)$$

For comparison purposes, the F1-measure combines Precision and Recall into a single framework. To get a more accurate performance interpretation, it is defined as a weighted harmonic mean of recall and precision.

$$F1 - meaure = 2 * \frac{Precision * recall}{precision + recall} \quad (5)$$

5. Results and Discussion

The suggested research study's findings are contrasted with those from earlier studies that used other aspect extraction techniques. Table 4 represents the empirical result. Precision, recall, and F-1 performance measures are used to express the outcomes.

Table 4. Results Comparison with the Baseline Studies

Study	Precision	Recall	F1-measure
[12]	74%	63%	76%
[26]	72.17%	73.43%	72.80%
Proposed Work	**85.14%**	**75.16%**	**79.83%**

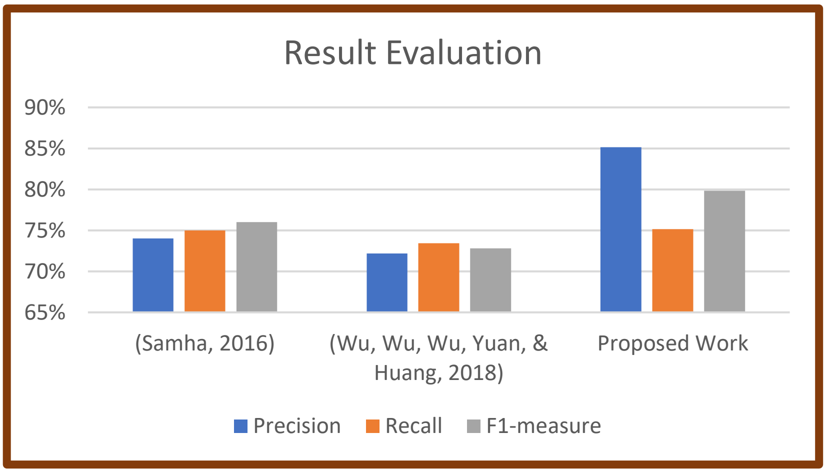

Figure 4. Results Comparison with the Baseline studies.

The outcomes unambiguously show that the suggested strategy has surpassed both of the baseline studies listed in Table 4. While comparison with the study [12], The proposed study improved the precision score by 11.14 percent, the recall score by 12.16 percent, and the F1-measure score by 3.8 percent. When compared to the study [26], an improvement of 12.97% was seen in the precision score, 1.73% was seen in the recall score, and finally, 7.03% was seen in the F-1 measure score. This improvement in the performance metrics is due to the syntactic structure of the dependency relation analysis where binary grammatical relations among the words in a sentence play an important role to describe their relationship. Furthermore, the aspect-opinion term pair is extracted by combining the TDRs and the extended TDR' with part of the speech patterns. The extracted aspect-opinion pair are pruned through the Sentiwordnet inspection process. In the final step polarity of the filtered aspect-opinion pair is estimated through the Sentiwordnet lexicon.

6. Conclusion and Future Work

This proposed research study intends to extract product features using the DRA technique with the rule-based algorithm. The study has experimented unsupervised approach in support of the objectives discussed earlier in the article. In experiments over the Amazon Product reviews dataset with 20,000 reviews selected from the Cell-Phone domain and 20,000 reviews selected from Amazon-Fine-Food reviews, The proposed research study has achieved a precision of 85.14 %, recall of 75.16%, and F1-measure 79.83 on the dataset. The limitations encountered in this work are that the authors have considered only SentiWordNet dictionary, and the length of reviews was restricted between 140-160 characters. Moreover, the feature pruning step can be further extended to consider not only syntactic features but also consider semantic features. In the Future, the authors intend to further analyze the different syntactic patterns and combinations to retrieve more complex linguistic patterns. Furthermore, the implicit aspects play an important role in aspect sentiment classification and needs sematic and more complex linguistic analysis, this arena will be explored in future work.

Data Availability Statement: Data can be provided on request.
Conflicts of Interest: The authors declare no conflict of interest.

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