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Object-Level Sentiment Analysis Use a Language Model

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Abstract

Sentiment analysis remains a prominent area of research in the natural language processing (NLP) community and holds significant practical value in domains such as commerce and education. Most existing approaches evaluate sentiments for a single object or product, typically categorizing them as positive or negative. However, when a text involves comparisons between multiple objects, it can be challenging to identify which sentiment or emotion is associated with which object. Few studies have addressed this issue, often stopping at evaluating emotions at the sentence level or for individual words related to aspects or objects. This study proposes an object-level sentiment analysis problem that produces a set of pairs or triples consisting of an object, aspect, and sentiment. Additionally, in texts expressing opinions or comments on a specific aspect, the aspect may be implied through references to the object without being explicitly mentioned. Identifying such implicit aspects is crucial, as it ensures no loss of information and enhances the efficiency of extraction of information in object-level sentiment analysis. The integration of implicit aspect identification and object-level sentiment analysis is the primary focus of this research. In recent years, many language models have been developed and effectively applied to various NLP tasks. Therefore, to address the proposed challenges, this study utilizes deep learning that incorporates language models combined with NLP methods such as parsing and dependency analysis, to achieve the desired output. Using language model and NLP techniques automatically generate training data for the learning model. The proposed method achieves an accuracy of 90%, making a substantial contribution to the field of NLP.

Keywords: Language Model, Deep Learning, Implicit Aspect, Sentiment, Object-Level Sentiment Analysis

1. Introduction

Currently, a large volume of comments on products available on the Internet exist, and the amount of textual data is increasing significantly. Texts such as comments, reviews, and opinions are referred to as "sentiment texts". Sentiment analysis is a popular problem in the field of natural language processing (NLP) and has been extensively studied using various approaches at text-[1], sentence-[2], [3], [4], and aspect-level analyses [5]. Document-level sentiment analysis aims to determine opinions expressed in a document. For example, when a product review is provided, the system determines whether the review conveys a predominantly positive or negative sentiment toward the product. At this level, each document is assumed to focus on opinions related to a single entity. Sentence-level sentiment analysis operates at the sentence level and determines whether a sentence expresses a positive, negative, or neutral opinion. Such analysis focuses on understanding sentiments within individual sentences. Aspect-level sentiment analysis directly examines opinions themselves. Neither document-level nor sentence-level analyses identify specific aspects that are liked or disliked by people. For example, we consider the sentence: "The iPhone's design is beautiful, but its battery runs out quickly." This sentence evaluates two aspects, "design" and "battery" of the entity "iPhone". The sentiments toward the "design" and "battery" are positive and negative, respectively. Aspect-level analysis aims to identify aspect-sentiment pairs and evaluate the sentiments associated with each aspect.To provide complete and detailed results in the form of pairs or triples representing the relationship among objects, aspects and emotions, this study proposes an object-level emotion analysis problem. Pairs or triplets help capture the aspects or features of products/services that influence sentiments. However, the focus of this study is currently limited to sentiment texts in

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English, and exploring their applicability to other languages in future research will be valuable. In sentiment texts, aspects are typically mentioned alongside sentiments. Sentiments and aspects can appear in the same or adjacent sentences such as the texts in figure 1. However, another challenge in sentiment analysis is the identification of implicit aspects. In the example: "I have just bought a smartphone. It is Sony Ericsson W890 and it is beautiful.", aspect of the Sony Ericsson W890 does the term "beautiful" refer to is unclear because the text does not explicitly provide this information. What aspects does the sentiment "beautiful" refer to? One sentimental word can refer to many different aspects, as figure 1 illustrates some emotional texts that include the word "beautiful" and the explicit aspects that it refers to. It may be one of these aspects, "photo", "design", "screen". Implicit aspects include those mentioned, but not explicitly stated in the text. To recognize implicit aspects, readers must apply their reading comprehension skills to analyze the textual context and the writer's method of expression. Numerous implicit aspect expressions include adjectives and adverbs used to describe or qualify specific aspects, such as "expensive" for price or "reliable" for reliability. From the texts in figure 1, based on the dependency parse tree and co-reference relationships of pronouns, pairs of sentiment-aspect of the word "beautiful" can be extracted. These pairs are converted into vectors for training data.

```
Line 817: Plus the color is very beautiful.
Line 833: I was looking for something different to my wife and this case its strong and beautiful
Line 2115: my car had to get used to it as it is old but after a few try's haven't had any issues with it si
Line 2234: The pictures come out real clear and beautiful after you send it via Email
Line 2698: Works great inside buildings.Clear beautiful color screen and camera
Line 4803:  My brother has this exact model and loves it, too.The phone has a beautiful color screen, easy t
Line 4813:  That said, the phone does have a beautiful inner LCD, the outer LCD is pretty bad
Line 5968:  I would have preferred the Motorola V3 Razor but that is still far too expensive and I have foun
Line 6432:  Therefore, the REALOOK 3D screen protector's edges and corners remain intact and look beautiful.
Line 6912: It's easily one of the classiest, most beautiful cases I've ever owned for a phone
Line 7080: (In fact, I've had far better luck with other Jabra BT products.) So, the design is beautiful and
Line 7681: It feels well made and has a beautiful quality generously proportioned screen; a definite plus fo
Line 9346:  It is beautiful and has great features but it keeps failing I have had 5 of these phones so far
Line 12209: This means that I can be watching a video or listening to music in beautiful stereo sound and if
Line 13697: Screen is absolutely beautiful, charging either by car jack or wall takes only minutes to get a
Line 17619: I just bought the Motorola KRZRZ K1 phone from China ,I was a bit leary ,but this phone is hard
Line 19251: I have quite a few cases for my beautiful HTC One, and they all have one huge problem; They hide
Line 19637: The installation is easy and the setup is so beautiful that Lexus technician asked me if I had i
Line 25926: Now I can open the music player and listen to beautiful music.This headset comes with a hidden m
Line 26895: The screen itself is beautiful, with bright colors and large size, perfect for web browsing and
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Figure 1. Examples of corpora include signs for identifying the implicit aspect that the word "beautiful" refers to.

By combining object-level sentiment analysis and implicit aspect identification, this study presents a deep learning approach that leverages contextual vectors and dependency parsing to extract pairs or triplets between objects, aspects, and sentiments. Implicit aspect identification in NLP poses challenges. Thus, this study employs deep learning techniques to detect cues or indicators of implicit aspects. Through training on a sentiment corpus specific to a domain, the proposed approach aims to identify patterns and signals for the automated and accurate detection of implicit aspects. Furthermore, deep learning is employed to determine an object classification model for aspects and sentiments within a specialized domain for object-level sentiment analysis.

The remainder of this paper is organized as follows. Section 2 reviews the relevant literature and previous studies in the field. Section 3 presents the proposed model for object-level sentiment analysis. Section 4 discusses the experimental results obtained by applying the proposed model. Finally, Section 5 concludes the paper, summarizes the findings, and suggests future research directions.

2. Related Work

2.1. Sentiment Analysis

Various methods have been developed to address sentiment analysis problems at the aforementioned three levels. Such methods include machine learning approaches [6], [7], deep learning techniques [8], [9], [10], [11], [12], [13], [14], lexicon-based methods [15], [16], and hybrid approaches [17], [18] that combine different methodologies. The simultaneous analysis of aspect-level sentiments within the context of overall sentiment analysis is a valuable and challenging task that requires capturing and evaluating the sentiments expressed toward specific aspects or features of the discussed object.

In opinion mining, the vast amount of information associated with an object including its attributes and aspects is crucial. To date, limited research has focused on object–aspect co-reference resolutions. The domain specifically aims to address linkages between objects and their associated aspects. Notably, two approaches have been proposed for object–aspect co-reference resolution [19], [20]. The objective of aspect co-reference resolution is to increase the accuracy and effectiveness of opinion-mining results by capturing the relationships between objects and relevant aspects.

To illustrate the importance of object and attribute co-reference resolution in opinion mining, we consider the following example: "I bought a Canon S500 camera yesterday. It looked beautiful. I took a few photographs at night. They were amazing." The pronoun "it" in the second sentence refers to the object "Canon S500 camera," while the pronoun "they" in the fourth sentence refers to the aspect of the object, namely, the "photos" taken. Resolving these co-references is essential for accurately understanding the expressed opinions. Without proper co-reference resolution, a significant amount of opinion-related information can be lost, and opinions can be incorrectly attributed to wrong entities. Therefore, effectively resolving object and attribute co-reference plays a crucial role in extracting and analyzing opinions in opinion-mining tasks.

Previous studies [19], [20]. have focused specifically on object–aspect co-reference in opinion texts involving one or more objects. Researchers [19] have adopted supervised learning on training data comprising manually annotated pairs of phrases representing object names or attributes. Contrarily, a study [20] employed a maximum entropy model for an object–aspect alignment classifier and utilized an integer linear programming inference procedure to achieve an optimal global result while considering specific constraints.

However, neither of the studies explicitly address the sentiments associated with an aspect and object. In the provided example, "amazing" and "beautiful" refer to the aspect "photos" and object "Canon S500 camera," respectively. Nonetheless, specific aspects of “beautiful” are not determined in such studies. Determining the sentiments of both aspects and objects is crucial in sentiment analysis. Resolving the problem requires an approach that can accurately identify the sentiments associated with each aspect and object. While the aforementioned studies contribute to object–aspect co-reference, they fall short of determining the sentiment of implicit aspects. The desired outcome of the problem is the extraction of pairs or triplets comprising an object, an aspect, and a sentiment from opinion texts that involve multiple objects. Thus, various approaches have been explored in this study, including unsupervised learning, deep learning, dependency grammar (DG), and sentiment ontology methods.

2.2. Implicit Aspects

Different approaches have been employed to identify explicit and implicit aspects in sentiment texts [21], [22], [23], [24], [25], [26]. Explicit aspects are typically represented by nouns, verbs, noun phrases, and verb phrases, whereas implicit aspects are often expressed through adjectives and adverbs. This study focuses on the challenging task of identifying implicit aspects and exploring diverse approaches, including clustering, machine learning, deep learning, and knowledge-based methods.

Clustering techniques have been used in studies [27], [28], [29] to extract implicit aspects. Such approaches involve identifying explicit aspects and grouping them into similar clusters, which are subsequently used to map implicit to explicit aspects. The aspect hierarchy approach [30] combines product specifications and customer reviews to generate a hierarchical organization that infers implicit aspects within review sentences. The method utilizes aspect hierarchy and opinion terms to identify implicit aspects.

Furthermore, machine learning techniques have been employed for implicit aspect identification. In a study [31], a naïve Bayes classifier trained using WordNet was used. First, a combination of corpus-and WordNet dictionary-based approaches was used to identify implicit aspect terms. Then, the classifier was trained to identify implicit aspects using the extracted implicit terms. Deep-learning approaches have been applied [32] using a deep convolutional neural network with a sequential algorithm to label words in sentences. Implicit aspects are identified by considering them as topics and matching sentiment words with the corresponding aspect.

A graph-based model was proposed in a previous study [33], utilizing the association between explicit aspects and opinion words to identify implicit aspects. A function was defined based on the association, and the edge weights of the graph were updated accordingly. By setting a gap threshold, a list of the most likely implicit aspects was extracted based on the measured co-occurrence values between aspects and opinion words. In a knowledge-based approach [34], co-occurrence-and similarity-based techniques were employed to identify implicit aspects. The study focused on extracting clues about the implicit targets of user opinions and identifying their true targets. The approach involved

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crafting rules to identify clues regarding implicit aspects and assigning aspects based on the clues extracted using a multi-level approach.

Indeed, the contexts of emotional words within sentences have not been fully explored using existing methods. Each word in a sentence possesses both left and right contexts, which can vary across sentences within a text. Additionally, relationships exist between sentences, such as anaphora and entity co-references, providing valuable cues in sentiment texts. To address such issues, we propose a deep-learning approach that leverages context vectors to identify implicit aspects, representing a cutting-edge technique in NLP.

Our approach involves utilizing grammar, syntax, and co-reference relationships to construct training data comprising sentiment–aspect pairs extracted from sentiment texts. Then, we employ deep learning techniques to classify sentiments that do not explicitly appear with aspects, thereby determining the implicit aspects. The utilization of deep learning is evident in the transformation of pretrained corpora into context vectors, which are subsequently used to filter and train the sentiment–aspect pairs in subsequent steps. The outcome of this process is the development of models capable of classifying the implicit aspects.

By incorporating context vectors and leveraging the power of deep learning, we aim to enhance the accuracy and effectiveness of implicit aspect identification. Our approach considers the linguistic structure of text, contextual relationships, and co-reference information, thereby enabling a more comprehensive analysis of sentiment texts and facilitating the classification of implicit aspects.

3. Object-level Sentiment Analysis Model (OSA)

The OSA model includes training and sentiment analysis phases, as shown in figure 2. The training phase, indicated by green and blue arrows, comprises the models CROAS [35] and IAI [36]. The sentiment analysis phase, indicated by red arrows, includes implicit aspect identification, object classification, and object-level sentiment analysis. The following sections describe the modules in detail.

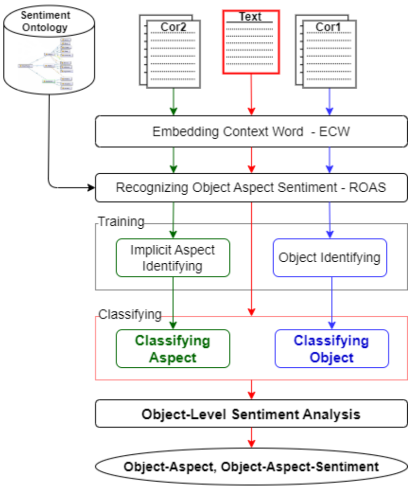

Figure 2. Architecture of object-level sentiment analysis.

3.1. Training phase

Cor1 and Cor2 are corpora that contain sentiment texts in specific domains and are used for training. Each text in Cor1 contains only one object, whereas Cor2 contains more than one object. The phase has two essential models before training what are embedding context words (ECW) and recognizing object aspect sentiment (ROAS).

3.1.1. Embedding Context Word

The ECW method converts words into real-number vectors by considering the left and right contexts of a word within a sentence. In a given corpus, each word has a unique vector in a distinct context. These vectors are generated through a pretraining module that provides the context vectors. The ECW module is important for generating numerical data for machine learning techniques, particularly artificial neural networks. Accordingly, the module uses BERT [37] to

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train Cor2, generating weights for embedding context words. Before the training process, the objects contained within Cor2 are preprocessed, and the BERT vocabulary assigns them the label Obj_Smart. In the OSA model, sentiment texts include objects with proper nouns, such as Samsung Galaxy A8 and Apple iPhone7. To preserve the meaning of object names when splitting words and phrases, phrases are replaced with a representative word, Obj_Smart. In addition to preprocessing the text before embedding words, performing parsing and DG analyses is essential. The step is crucial to support the creation of input data for the training module in the OSA model (figure 2).

3.1.2. Recognizing Object, Aspect, and Sentiment

Recognizing object, aspect, and sentiment (ROAS) is a module that recognizes object, sentiment, and aspect words, and labels semantics based on a sentiment ontology (SO) [38]. The module identifies words in texts that appear in SO and determines the class to which the words belong. SO is the knowledge base and it is used for classifying semantics, as figure 3. The architecture of SO comprises three conceptual classes: object (OBJ), aspect (ASP), and sentiment (SEN). Individuals in SO can be entities or specific objects, including objects such as "Samsung Galaxy J3" or "Oppo A37", aspects such as "price" or "design," and sentiments such as "cheap" or "beautiful."

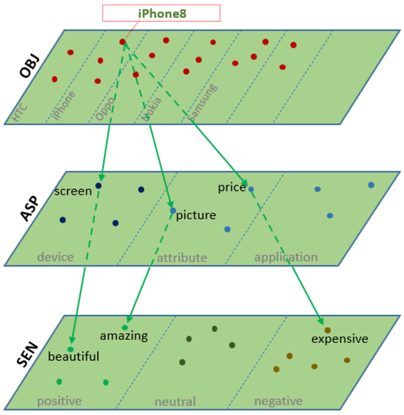

Figure 3. Archirecture of sentiment ontology.

The SO has various capabilities, including identifying implicit aspects of sentiments, identifying aspects related to their objects, resolving entity co-reference represented by noun phrases (isCore), and determining the positive or negative orientation of sentiments. Thus, SO facilitates the identification and understanding of the relationships between objects, aspects, and sentiments.

3.1.3. Training

In order to have data for the training process automatically from the original corpus, this research applies basic techniques in natural language processing, namely parser and dependency grammar. Parser and dependency grammar analysis involve analyzing the grammatical structure of sentences and determining the relationships between words, assisting in understanding syntactic dependencies and hierarchical structures within a sentence. The goal of parsing, syntactic analysis, is recover the structure described by a series of tokens, such as nn (noun), nnp (proper noun), adj (adjective). The goal of the OAS model is to extract objects (nnp), aspects (nn) and sentiments (adj, adv) for sentiment analysis. By parsing the text and extracting dependency relationships, capturing connections and dependencies between words, such as subject-verb relationships, modifiers, and other syntactic relationships, is possible.

The process plays a vital role in preparing the input data for the training modules of the OSA model. It helps structure text and represent it in a format suitable for further processing, such as word embedding and training neural networks. By incorporating parser and dependency grammar analyses, the OSA model effectively captures linguistic features and dependencies within a text, enabling better performance and accuracy in subsequent tasks. Dependency grammar analysis is instrumental in identifying sentiment-aspects, aspect-objects, and sentiment-object pairs. It leverages various dependent grammatical relationships that exist between sentence components. These relationships are defined by specific patterns, such as "amod (nn, adj)" and "advmod (vb, adv)," where "nn," "adj," "vb," and "adv" represent noun, adjective, verb, and adverb, respectively.

By analyzing the dependency grammar relationships, the module can determine the pairs that are relevant within a specific domain. For example, the relationship between an adjective and a noun that represents a sentiment–aspect pair, or the relationship between a noun and a pronoun that represents an aspect–object pair, can be identified. In addition, the module identifies pairs that involve sentiments and objects. Dependency grammar relationships provide valuable insights into the connections and dependencies between words in sentences. By leveraging these relationships, the module can extract meaningful pairs pertinent to a specific domain under consideration, allowing for a more precise and focused analysis of sentiments, aspects, and object relationships within the text.

The training phase involves two subproblems: Implicit aspect identification (IAI) [36] for sentiments and object identification for aspects and sentiments (CROAS) [35]. These problems are designed to facilitate the identification set of pairs or triples comprising objects, aspects, and sentiments, thereby supporting object-level sentiment analysis. The subproblem determines the implicit aspects of IAI with the input being the Cor2 corpus, specialized in containing the aspects and emotions of objects mentioned in the text. They include traces and latent knowledge in the corpus from which the machine can learn, thereby constructing a model to identify the implicit aspects of emotional words. The key issue in the training phase is the training dataset, which is denoted as DA. DA includes pairs of emotional aspects extracted from the Cor2 corpus that contains both syntactic and semantic relationships in a specialized domain, thereby forming the foundation of natural language processing tasks. The extraction of such emotion–aspect pairs is performed using the creating data DA module [36] , with the support of the ECW and ROAS modules. The DA dataset comprises two subsets. The first subset, DA1s, consists of datasets that individually correspond to each emotional word. The second subset, DA2s, comprises datasets that correspond to each sentiment word, specifically, those that refer to aspects as attributes.

After obtaining the emotional aspect dataset DA, the model is trained on the DA dataset using a two-layer neural network (figure 4) with multiple inputs and outputs (the training algorithm in [36]), resulting in the weight set W0. The number of outputs depends on the number of aspects in the sentiment ontology. With the ultimate goal of IAI being to determine the best-performing implicit aspect (W2s) classification models, W0 is fine-tuned on the DA1s dataset to produce W1s (Tuning1 module). Furthermore, Tuning2 fine-tunes W1s on the DA2s dataset to obtain the optimal W2s model. The architectures of Tuning1 and Tuning2 are illustrated in figure 5.

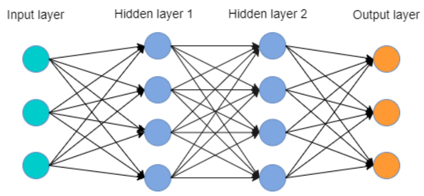

Figure 4. Architecture of the artificial neural network.

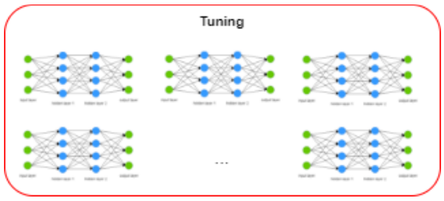

Figure 5. Architecture of the Tuning1 and Tuning2 modules.

The second subproblem, object identification for aspect and sentiment (O4AS) with input from the specialized domain-specific Cor1 corpus repository containing emotional words related to the aspects of an object mentioned in the text. The objective of this problem is to determine a classification model for identifying objects based on the emotion–object and aspect–object relationships within Cor1. Similar to the IAI subproblem, the training dataset for O4AS, denoted as DO, is extracted based on the syntactic and semantic relationships of emotion and aspect objects using the support of ECW and ROAS modules. The DO dataset is trained on a single-layer perceptron (figure 6) with multiple inputs and outputs (the algorithm 1 in [35]), resulting in weight set W.

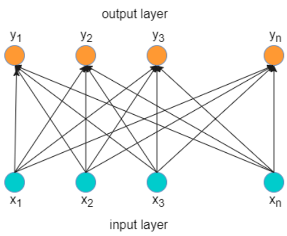

Figure 6. A single layer perceptron network.

Both the input and output nodes are n-dimensional real-valued and transformed by the ECW. The output is calculated according to (1) as

$$\hat{y}_i = \sum_{j=1}^{n} w_{ij} x_j + b_i \quad (1)$$

O4AS determines the object classification model.

3.2. Sentiment Analysis Phase

In figure 2, the sentiment analysis phase is indicated by red arrows. This phase uses a text (Doc) consisting of multiple objects specified within a domain as the input. The output of the phase is a set of pairs or triplets, each of which represents the relationship between an object and aspect, object and sentiment, aspect and sentiment within Doc. To generate the pairs or triplets, the phase incorporates the following modules: classifying implicit aspect (CIA), classifying the object (CO), and object-level sentiment analysis (OLSA).

CIA is a module specifically designed to identify aspects of sentiments that do not explicitly refer to any aspect mentioned in Doc. The module utilizes the output of the IAI subproblem to determine the implicit aspect. CIA returns pairs of aspect–sentiment PA. The CO module is responsible for classifying the sentiments and aspects in a document, as demonstrated in Algorithm 2 [35]. The algorithm generates pairs of object aspects and object sentiment, denoted as PO. The OLSA module is the final component of the OSA model, which serves the purpose of generating pairs or triads of object aspect sentiments. Algorithm 3 [35] is specifically designed to combine the previously acquired pairs of object-aspect, object-sentiment and aspect-sentiment and deduce pairs of object-aspect or triplets of object-aspect-sentiment using the co-reference graph G [38].

4. Experiment

4.1. Dataset and Hyperparameters

This subsection discusses the dataset, settings of the implemented architecture hyperparameters, and experimental environment of the OSA model. The datasets used in the training phase of the OSA model are listed in table 1. The Cor1 and Cor2 corpora were first proposed by Amazon. Both corpora were datasets of the O4AS and IAI problems. The domains of both corpora were sentiment texts that referred to smartphones. The texts mentioned aspects of sentiment, opinions of an object, or more. Cor1 contained 90,572 texts in which each text mentioned only one object. Cor2 included 389,103 texts in which each text mentioned only one or more objects. The numbers of samples, training and testing samples are shown in table 1.

Table 1. Dataset of the training phase of the OSA model

Corpus (1)	Number of texts (2)	Number of samples (3)	Training Samples (4)	Testing Samples (5)
Cor1	90,572	9,456	8,510	946
Cor2	389,103	69,905	64,374	5,531

First, each text in the corpora was converted into real-number vectors and extracted into samples corresponding to the third column of table 1. Subsequently, the data were divided into two datasets: training and testing (the fourth and fifth columns). The training hyperparameters of both the IAI and O4AS are listed in table 2, including the epochs, batch size, learning rate, and number of steps per epoch. All values were selected based on the experimental results of the model. The modules were deployed in a Colab Google environment with a GPU and an 8-core TPU.

Table 2. Hyperparameters of IAI and O4AS

Hyperparameter	IAI	O4AS
Epochs	500	100
Batch size	32	16
Learning rate	1e-2	1.0
Number of Steps per epoch	2012	591

4.2. Results and Evaluation

This section first presents the training results for the IAI and O4AS subproblems. Then, the results of the OSA model are presented. For the IAI problem, the results after tuning the modules with data DA1 and DA2 are listed in table 3. Among these datasets, 5 datasets corresponding to the 5 most frequently appearing emotional words in Cor2 corpus were introduced. The accuracy of Tuning2 (table 3) was higher than that of Tuning1.

Table 3. Result of the Tuning modules

Sentiment	Training data		Accuracy of Tuning	
	Tuning1 (DA1)	**Tuning2 (DA2)**	**Tuning1**	**Tuning2**
Great	9,582	4,584	0.922	0.983
Good	7,855	3,252	0.931	0.986
Nice	3,628	1,861	0.937	0.975
Light	1,692	1,162	0.851	0.961
Fast	1,226	418	0.860	0.973

The training results of the O4AS module for Cor1 are presented in table 4. As the number of iterations increased, the Euclidean distance between the output and desired results gradually decreased, indicating the effectiveness of the O4AS module. To demonstrate the effectiveness of the proposed OSA model and its constituent modules, we present experimental results for the following selected examples.

Table 4. O4AS training module results on Cor1

Steps	Minimum	Maximum	Average
300,000	0.0386	0.9813	0.4360
400,000	0.0399	0.9804	0.4324
500,000	0.0517	0.9795	0.4294

Example 1. Document Doc1 and Doc2. Doc1. "I gave my Nokia Lumia 822 to my wife and bought myself a Sony Ericsson W890 two days ago. The Ericsson W890 is beautiful. The battery is amazing. But what I really appreciate is the speaker producing good sound and its 128 g storage". Doc2. "I gave my Sony Ericsson W890 to my wife and bought myself a Nokia Lumia 822 two days ago. The Nokia Lumia 822 is beautiful. The battery is amazing. But what I really appreciate is the speaker producing good sound and its 128 g storage".

Example 1 illustrates the effect of changing the positions of objects within the same content, and the resulting classification of aspects and emotions that are contextually appropriate in the text. Doc1 and Doc2 differ in the positions of the objects mentioned in the text (Nokia Lumia 822, Sony Ericsson W890), whereas the remaining words and phrases remain unchanged. The classification results for emotional words and aspects in Doc1 and Doc2 are consistent with the positions of the objects, as illustrated in figure 7. In Doc1, the aspects and sentiments refer to "Ericsson W890", whereas in Doc2, the object is replaced by "Nokia Lumia 82". Consequently, the aspects and sentiments in Doc2 that are like those in Doc1 is associated with "Nokia Lumia 822".

```
Doc1:
beautiful - Ericsson_W890 = 0.23241816978309626
battery - Ericsson_W890 = 0.2467261373140627
amazing - Ericsson_W890 = 0.2455385639229403
appreciate - Ericsson_W890 = 0.2553074967442743
speaker - Ericsson_W890 = 0.24521058408433904
good - Ericsson_W890 = 0.2565177207974428
sound - Ericsson_W890 = 0.2478274083876697
storage - Ericsson_W890 = 0.24321880800407641

Doc2:
beautiful - Nokia_Lumia_822 = 0.23241816978309626
battery - Nokia_Lumia_822 = 0.2467261373140627
amazing - Nokia_Lumia_822 = 0.2455385639229403
appreciate - Nokia_Lumia_822 = 0.2553074967442743
speaker - Nokia_Lumia_822 = 0.24521058408433904
good - Nokia_Lumia_822 = 0.2565177207974428
sound - Nokia_Lumia_822 = 0.2478274083876697
storage - Nokia_Lumia_822 = 0.24321880800407641
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Figure 7. Classifying module results on Doc1 and Doc2.

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Considering the next example, Example 2. Example 2: "I like my Galaxy Note8. The display is clear, the camera is better on the Nokia Lumia, and the performance is better on the Ericsson W890". Three objects in, Galaxy Note8, Nokia Lumina, and Ericsson W890, are identified. The result of classifying the object is Galaxy Note8 in Example 2, as illustrated in figure 8.

```
like - Galaxy_Note8 = 0.2906019156287734
display - Galaxy_Note8 = 0.24727460309277535
clear - Galaxy_Note8 = 0.24894856479072452
camera - Galaxy_Note8 = 0.24674539179535082
better - Galaxy_Note8 = 0.24491422960114725
performance - Galaxy_Note8 = 0.2609073613254154
```

Figure 8. Classifying module results on Example 2.

The text in Example 2 has aspects and sentiments: "like", "display", "clear", "camera", "better", "performance". In the first sentence, the speaker "like" the object "Galaxy Note8", and in the following sentences, the speaker clearly states their opinion about the aspect "display" display "clear", and the two aspects "camera" and "performance" were "better" compared to the two objects "Nokia Lumia" and "Ericsson W890". Example 2 demonstrates that the OSA model (figure 2) accurately classifies objects based on emotional words and aspects.

Considering Example 1 with Doc1 and Doc2: in Doc1 and Doc2, an implicit aspect exists that is the sentiment "beautiful" that does not refer to any specific aspect in the text. To determine the implicit aspect for the sentiment word "beautiful", the aspect classification module classifies "beautiful" as the aspect "design". The results after object classification, determination of the implicit aspect, and results of OSA in Doc1 of Example 1 are shown in figure 9. In which, edges of the graph indicate the method identified vertices, such as IAI, DG or O4AS.

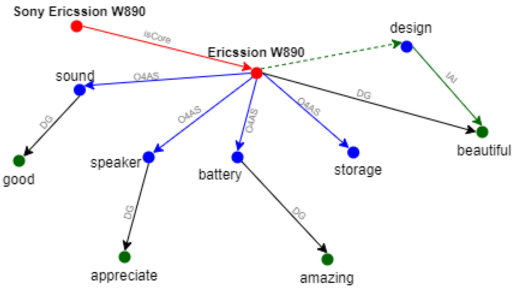

Figure 9. Result of OSA on Doc1.

The effectiveness of the proposed OSA model was evaluated using the following method: Let tp denote the number of correctly classified triplets of objects, aspects, and sentiments in a classified dataset; Let fp denote the number of incorrectly classified triplets of objects, aspects, and sentiments in a classified dataset; Let fn denote the number of incorrectly classified triplets of objects, aspects, and sentiments in the expectation-classified dataset; The precision P, recall R, and F1 metrics were calculated using (2), (3), and (4), respectively.

$$P = \frac{tp}{(tp+fp)} \quad (2)$$

$$R = \frac{tp}{(tp+fn)} \quad (3)$$

$$F1 = \frac{2\times P\times R}{(P+R)} \quad (4)$$

The evaluation dataset consisted of 1000 sentiment texts on smartphones. Table 5 presents the results for the accuracy, recall, and F1 scores for the OSA model. In this table, OSA* and OSA** correspond to OSA without and with the use of IAI, respectively, to identify implicit aspects. With the parameters from table 2, OSA** achieved an accuracy of 90.64% and a recall of 88.33%, outperforming OSA*. The results of table 3 indicate that the accuracy of IAI for emotional words is mostly above 90%. Table 5 shows that the accuracy of object-level sentiment analysis (OSA*) is 88%. When IAI is combined with OSA, the OSA** result is 90.64%. We used preinstalled environments such as the Keras library for training; thus, information on cross-validation and dataset splits was applied according to the Keras library. This is a popular and effective library for training models. Thus, the effectiveness of the machine-learning

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method applied to the OSA model combined with deep learning in the IAI aspect identification model was demonstrated.

Table 5. Evaluation results of OSA on 1,000 smartphone comment texts

Method	Precision %	Recall %	F1
OSA*	88.00	85.76	86.87
OSA**	90.64	88.33	89.47

5. Conclusion

Sentiment analysis has been a challenge in NLP, and object-level sentiment analysis is no exception. Sentiment analysis has received significant attention from the NLP community, and various approaches have been proposed. However, very few publications have provided comprehensive and detailed results for the three components of object-aspect-sentiment. Building upon the co-reference resolution, syntax and sentiment ontology in sentiment analysis, this study proposes a deep learning approach based on contextual text analysis to address OSA. The results of the pairs or triplets help readers clearly understand the sentiment analysis outcomes. In addition to identifying triplets, this study addresses another challenging aspect in object-level sentiment analysis, which involves determining implicit aspects for sentiment words that appear in the text but not explicitly mentioned as an aspect. The proposed method demonstrates the effectiveness of deep learning on specialized domain corpora combined with syntactic and semantic processing techniques in NLP. To increase model accuracy, the OSA model can replace BERT with large language models, such as GPT-3 and GPT-4. Additionally, the proposed model is extended to various domains and languages for further investigation.

6. Declarations

6.1. Author Contributions

Conceptualization: T.T.L., T.T.P.; Methodology: T.T.L.; Software: T.T.L.; Validation: T.T.L., T.T.P.; Formal Analysis: T.T.L., T.T.P.; Investigation: T.T.L.; Resources: T.T.P.; Data Curation: T.T.P.; Writing Original Draft Preparation: T.T.L., T.T.P.; Writing Review and Editing: T.T.P., T.T.L.; Visualization: T.T.L.; All authors have read and agreed to the published version of the manuscript.

6.2. Data Availability Statement

The data presented in this study are available on request from the corresponding author.

6.3. Funding

The authors received no financial support for the research, authorship, and/or publication of this article.

6.4. Institutional Review Board Statement

Not applicable.

6.5. Informed Consent Statement

Not applicable.

6.6. Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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