



# An Ontology-Based Approach to Enhance Explicit Aspect Extraction in Standard Arabic Reviews

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**Abstract:** Currently, one of the most important and difficult areas of research is Arabic Sentiment analysis. Aspect extraction is the most important task in aspect-based sentiment analysis. In this work, we propose an aspect-based sentiment analysis approach for Arabic language. The basic idea of the proposed approach is to use the description logics to identify explicit aspects as well as their polarities. This approach was evaluated using the publicly available human annotated Arabic dataset (HAAD) based on Semantic Evaluation 2014 workshop (SemEval-2014) along with its baseline experiments conducted by HAAD providers. Experimental results showed that the proposed approach significantly improves the performance compared with baseline approach. The F-measure was improved by 19% and 55% for the aspect terms extraction and aspect term polarity tasks respectively.

**Keywords:** Opinion Mining, Arabic Sentiment Analysis, Aspect Level, Polarity, Explicit Aspect, Description Logics

## 1. INTRODUCTION

With the growth of user-generated content on the social web and the eminent progress in web interaction, Sentiment Analysis (SA) has become an integral part of social media management for enterprises. A classic task of SA mainly involves classifying the overall opinion polarity expressed in a document (document level sentiment analysis) or in a sentence (sentence level sentiment analysis). Another, more refined task called aspect-based SA (for short ABSA) deals with detecting opinions on a specific aspect. Aspects also known as opinion targets are topics subject to opinion expression [1].

In the review sentence (its equivalent in English) *الرواية حزينة قد لاتستحق عناء القراءة* (A sad novel may not be worth the trouble of reading), *رواية* (novel) is the aspect that is expressed with a negative sentiment. Aspect extraction is an important subtask, and can refer to either implicit or explicit aspects.

ABSA also known as feature-based opinion mining in [2] is the task of mining opinions about specific aspects [3]. ABSA was first presented as a shared task in SemEval2014 for English texts [4].

Recently, SA of Arabic user-generated content has become one of the essential research fields [5]. Research on SA in Arabic Language mostly focuses on both the document level and the sentence level [6]. But few studies exist for ABSA. On the one hand, ABSA's research is

mainly based on the lexical approach, on the other hand, ABSA's tasks are difficult because of the variety of semantics of the opinions expressed [7], as well as the polarity of the opinion-carrying words used to describe them. It is therefore necessary to improve the sentiment analysis through semantic aspects. This research focuses on ABSA for the standard Arabic Language. The motivation of this choice is double-handed: on the one hand, both document level and sentence level do not find what exactly people liked and didn't like [8]. On the other hand, for opinions to be exhaustive, analysis should be supplied for each aspect or feature of the entity [9].

The task, which relates to SemEval2014-ABSA [4], includes four subtasks: aspect term extraction (T1), aspect-terms' polarity identification (T2), aspect category identification (T3), and aspect category polarity (T4). Our work considers only the first two ABSA subtasks T1 and T2. To this end, we propose to employ Description Logics (DL) to describe the ontology combined with linguistic rules.

Our contribution is twofold:

- First, the construction of domain ontology by using DL to describe terminological knowledge. To our knowledge, this is the first research work in Arabic that addresses ABSA with DL.
- Second, the identification of the opinion target by means of DL combined with linguistic rules.



To evaluate the proposed approach, HAAD the first ABSA dataset for Arabic language was used. HAAD was developed by Al-Smadi et al. [10] in 2015, and was annotated using the SemEval2014 Task4 dataset schema. HAAD consists of books reviews selected from the large scale Arabic book reviews (LABR) dataset developed by Aly and Atiya [11].

The rest of this paper is organized as follows: Section 2 discusses related works. The proposed approach is presented in Section 3. Section 4 presents and discusses the results obtained with the two subtasks T1 and T2. Section 5 provides an analysis and explains the causes of the errors generated by the proposed system. Finally, conclusions for this work are made in section 6.

## 2. RELATED WORKS

In this section, we will focus mainly on the ABSA studies that have been carried out on the Arabic language. As described in the introduction section, Arabic opinion mining has not received much attention in comparison to English, but most researches were carried out at document level or sentence level. The studies focusing on ABSA are recent for Arabic, in fact, Al-Twairesh et al [12] point out that until 2015, no work on ABSA has been done on the Arabic language. ABSA is carried out by using two approaches: Machine Learning and Lexicon.

In machine learning approaches where prior labeling of aspect and sentiment terms in the dataset is required, several supervised learning techniques are used [13]. Tamchyna and Veselovská [14] utilized neural networks to extract aspect category in many languages like Arabic, Dutch or English. Whilst, Al-Smadi, et al. [15] investigated several supervised learning techniques to extract aspect terms and their polarities, the results show that J48 performs the best for aspect term identification. Whereas for in polarity identification, CRF and NB are better. The same authors propose in [16] an improved supervised machine learning approach to extract aspect terms and their polarities. Three tasks are considered: aspect category identification, opinion target expression and sentiment polarity identification. Results show that the proposed approach outperformed the baseline approach, and the overall enhancement is around 53% for the first task, around 59% for the second task, and around 19% for the third one. Behdenna et al. [8] proposed a machine learning approach to extract opinion target from Arabic tweets. Several feature forms are examined to evaluate their impact on the performance of extracting opinion targets using two classifiers, SVM and Naïve Bayes. The results show that stemming combined with the removal of stop words significantly improves the performance of the classification.

One of the recent trends in SA is the use of deep learning methods. Al-Smadi et al [17] used bidirectional LSTM with a CRF classifier to identify opinion target and LSTM to classify aspect sentiment polarity. Whereas El-Kilany et al. [9] trained a bidirectional LSTM with conditional random fields (CRF) classifier to extract the entities from

Arabic tweets.

Lexicon-based approaches use an opinion lexicon [18]. Al-Smadi et al [19] has developed several lexicon-based approaches to address two ABSA sub-tasks (T3 and T4). They report that they are the pioneers of ABSA in Arabic, as they developed an Arabic Human Annotated Data Set (HAAD), consisting of reviews of Arabic books, and made it publicly available [10]. Alkadri and ElKorany [20] used the semantic of ontology and lexicons to identify aspect terms and their polarities. In [21], the authors constructed a prototype for SA of Arabic tweets using Arabic Opinion Lexicon and Arabic Tweet Sentiment Analyzer. Abd-Elhamid et al [22] proposed a feature-based SA approach for mining Arabic user generated reviews; the sentiments and features were extracted automatically from a set of unannotated reviews using a set of linguistic rules. Ismail et al. [23] proposed a generic approach for extracting the aspects of entities and their opinions, this approach relies on the idea that the entities aspects and their opinion-bearing words are usually correlative; these words are used to orient the process of extracting the entity aspects, for this, the authors added sentiment tags on the roots and patterns of an Arabic lexicon.

Finally, some works focused on the development of annotated corpus required for all tasks related to the ABSA. As a result of limitation in availability of appropriate datasets, the HAAD dataset, developed by Al-Smadi et al. [10], was the first publicly available ABSA dataset in the Arabic language. Whilst Al-Sarhan et al. [24] provided a benchmark of annotated Arabic dataset. They proposed a baseline approach for four ABSA sub-tasks, and a lexicon-based approach for aspect term extraction and aspect term polarity. Areed et al [25] present an Arabic ABSA corpus for government mobile apps Arabic reviews, and proposed a combined approach to extract aspects and classify sentiments by adopting lexicon-based and rule-based approaches.

As shown in Table I, the major approaches used in Arabic ABSA were mainly developed for MSA and few works addressed the dialects that used lexicon based approach. On the whole, it should be noted that studying both MSA and dialect is more relevant than studying MSA on its own.

Moreover, we note that the most current works on Arabic ABSA used lexicon-based approach for extracting aspects and determining the polarities. Owing to high semantic of the opinions expressed and the polarity of the opinions expressed to depict them, however, the ABSA tasks are very difficult [7]. It is therefore necessary to move on semantic aspect-based sentiment analysis.

In aspect-based sentiment analysis, domain ontology is a very important knowledge base to identify entities, aspects and opinion [26]. This paper introduces a semantic method to classify opinion at aspect level. To recognize aspects and infer aspect-associated sentiment, the proposed approach



TABLE I. SUMMARY OF RELATED WORKS  
(Acc: ACCURACY; F1: F-MEASURE)

Ref	Objectives	Data Source	Language Variation	Approach	Evaluation
[8]	Extract the opinion target	Mobile phone brand tweets	MSA	Machine learning(SVM, NB)	Acc=86% F1=87.5%
[9]	Detecting sentiment targets	Tweets	MSA	Deep learning	F1=72.6%
[10]	Provide a benchmark of human annotated Arabic dataset (HAAD)	HAAD (reviews of Arabic books)	MSA	Lexicon	T1:F1=23.39% T2: Acc=29.70% T3: F1= 15.2% T4: Acc=42.6%
[14]	Identify all aspect categories	Hotels' reviews	MSA	Machine learning (Neural network)	F1= 52.59%
[15]	aspect term extraction and aspect-terms'polarity identification	News posts and Facebook comments about the 2014 Gaza Attacks	MSA	Machine learning (CRF, J48, NB, IBk)	T1: The best ML: J48 F1=81.7% T2:The best ML: CRF Acc= 86.5%
[16]	Aspect Category Identification and Sentiment Polarity Identification	HAAD	MSA	Machine learning (NB, K-NN, SVM)	Aspect Category Identification: F1=53% Opinion Target Extraction: F1=59% Sentiment Polarity Identification:Acc=19%
[17]	Aspect opinion target extraction, and aspect sentiment polarity identification	Hotels' reviews	MSA	Deep learning (LSTM, Bi-LSTM-CRF)	Aspect opinion target extraction:F1= 69,98% aspect sentiment polarity identification Acc=82.70%
[19]	Aspect category identification Aspect category polarity identification	HAAD	MSA	Lexicon	T3:F1= 23.8% T4: Acc= 88.4%
[20]	Develop a framework for semantic feature-based opinion mining	Hotels' reviews	MSA	Lexicon	Feature polarity identification: Acc= 67.5% Opining mining:Acc= 95.5%
[21]	Identification of aspects and Classification of Opinions.	Arabic tweets for restaurant services	MSA	Lexicon	Subjectivity : F1= 93.9% Polarity:F1=89.85% Target identification: F1=73.21% Acc=87.5%
[22]	Feature-based sentiment analysis approach	Reviews	Standard or dialectal Arabic.	Lexicon	
[23]	Extraction of entity aspects and their opinions	movie and restaurant reviews	MSA	Lexicon	entity-level: Acc=96% Aspect-level: F1=79%.
[24]	Provide a dataset of Arabic text in news domain	Facebook posts about Gaza attacks 2014	MSA	Lexicon	T1: F1= 51.4% T2:Acc=67.3%
[25]	Present an Arabic ABSA corpus, Extraction of aspects and Classification of sentiments.	Government smart apps reviews	mixture of MSA and multiple dialects	Lexicon	Acc= 96.57% F1= 92.50%

used the ontology (Description logics (DL) were used to describe the ontology).

### 3. PROPOSED APPROACH

Most research's effort in sentiment analysis deals with English texts but few studies focus on Arabic language. This paper addresses ABSA for the standard Arabic language. According to SemEval2014-ABSA [4], the task has four subtasks: aspect term extraction, aspect-terms' polarity identification, aspect category identification, and aspect category polarity. Only the two first subtasks are considered in this research. Those subtasks are difficult to accomplish [7]. To cope with these challenges, in this research, a semantic approach based on domain ontology is proposed to support Arabic ABSA of reviews.

Thus, the aims of this work can be fixed as follows:

- Extraction of the aspect terms. Whether it is an entity recognized, in this case its aspects on which opinions have been expressed must be extracted.
- Identification of the opinion polarity for each aspect detected.

This work is an extension of the published paper [27]. The old version focused exclusively on the design of the approach. At this point, the implementation has not been completed.

Compared to the old version, this research has more additional information, for example, section 3, is enriched with more details on the design of the approach. In term of evaluation, we added experiment section to discuss the results of implementation of the approach using the HAAD corpus. We also included comparison with the baseline approach [10] and discuss the limitations and errors of the proposed approach.

As mentioned in [27], the ontology is proposed to extract aspect terms and solve the strong semantic variability of opinions expressed.

The proposed approach uses DL to describe our domain ontology. The motivation to use DL is twofold: the entities and their aspects are described by concepts, and roles [28] and DL is based on formal semantics and logic [29].

The architecture of the proposed Semantic ABSA System is shown in Figure 1.

This architecture consists of the following two phases:

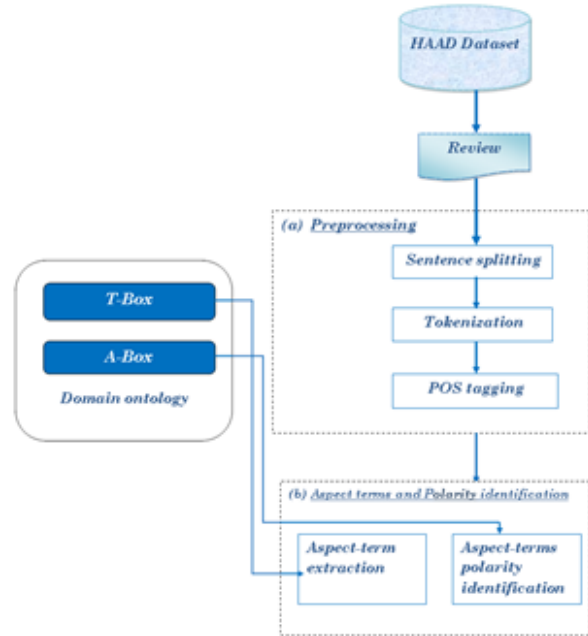


Figure 1. Proposed system architecture

#### A. Ontology development

Ontology is used to model the terms and the relations between these terms [30]. The goal of using ontology in ABSA is to identify entities, aspects and opinions [26].

To demonstrate the contribution of this research, a choice is made for a relatively small ontology in the book domain. We targeted this field because we found that among the corpuses that meet our needs, there was the corpus of book reviews [10] (HAAD corpus). But on the other hand, Arabic ontology on book, to our knowledge, is not available. For this reason, we have chosen the universe of literature (books, writers) as an example of application to build domain ontology. The latter can then be used to identify aspects and their polarities in book reviews written in Arabic.

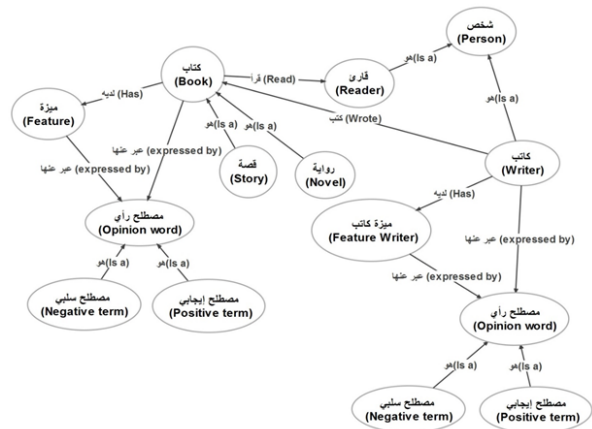


Figure 2. A snapshot of Book Ontology



The ontology language recommended by W3C is Web Ontology Language (OWL). This language offers three sub-languages: OWL-Lite, OWL-DL and OWL-Full. The OWL-DL language is a variant of the description logic (DL) [31]. We have chosen to represent our ontology with OWL-DL because it is suitable for the representation of ontologies needing expressivity power. DL uses two components: T-Box and A-Box. T-Box, represented by a set of axioms, defines domain concepts and their semantic relations while A-Box includes instantiations of those concepts and relations.

Building ontology is a difficult process. Automatic and semi-automatic generation of ontology from a domain corpus is a research challenge in the Semantic Web. Many tools have been created for that task (e.g., Kaon , Ontogen , Text2Onto [32], etc). However, as far as we know, there are no tools for the building of ontologies in Arabic. For this reason, we decided to create manually the ontology from the domain corpus (HAAD). First, we define the structure of the ontology and generate all of the terms to be used in this ontology. Then, the ontology was created manually using Protégé and exported into OWL-DL. In addition to the hierarchical relation "is a", other semantic relations (has, expressed by...) have been created to link the different concepts.

T_BOX	It's equivalent in English
<p>كتاب ≡ T</p> <p>شخص ≡ ا كتب كتاب</p> <p>شخص ≡ ا قرأ كتاب</p> <p>سليمي ا ايجابي مصطلح ≡ رأي مصطلح</p> <p>مصطلح</p> <p>ا ≡ سليمي مصطلح ا ايجابي مصطلح</p> <p>ميزة. لديه ≡ ا كتاب</p> <p>رأي مصطلح. عبر عنها ≡ ا كتاب</p> <p>رأي مصطلح. عبر عنها ≡ ا ميزة</p> <p>ميزة-كاتب. لديه ≡ ا كتاب</p> <p>رأي مصطلح. عبر عنها ≡ ا كتاب</p> <p>رأي مصطلح. عبر عنها ≡ ا ميزة-كاتب</p> <p>كتاب ≡ قصة</p> <p>كتاب ≡ رواية</p>	<p>Book ≡ T</p> <p>Writer ≡ ا Wrote. Book ≡ Person</p> <p>Reader ≡ ا Read. Book ≡ Person</p> <p>Opinion word ≡ Positive term ⊆ Negative term</p> <p>Positive term ⊆ Negative term ≡ ⊆</p> <p>Book ≡ ا Has. Feature</p> <p>Book ≡ ا expressed by. Opinion word</p> <p>Feature ≡ ا expressed by. Opinion word</p> <p>Writer ≡ ا has. Feature Writer</p> <p>Writer ≡ ا expressed by. Opinion word</p> <p>Feature Writer ≡ ا expressed by. Opinion word</p> <p>Story ⊆ Book</p> <p>Novel ⊆ Book</p>
A_Box	It's equivalent in English
<p>(جميل) مصطلح ايجابي</p> <p>(متع) مصطلح ايجابي</p> <p>(ضعيف) مصطلح سلبي</p> <p>(متدفقة) مصطلح ايجابي</p> <p>(مؤلمة جدا) مصطلح سلبي</p> <p>(احمد حلمي) كاتب</p>	<p>Positive term(nice)</p> <p>Positive term(enjoyable)</p> <p>Negative term(weak)</p> <p>Positive term(gushing)</p> <p>Negative term(very painful)</p> <p>Writer(Ahmed Helmy)</p>

Figure 3. T-BOX AND A-BOX OF OUR BOOK ONTOLOGY

Figure 3 depicts the T-Box and A-Box of this ontology.

- T-Box allows introducing the concept axioms and role axioms. There are 9 top level concepts which

are associated to book domain: ميزة (Book), ميزة (Feature), قصة (story), رواية (novel), شخص (Person), قارئ (reader), كاتب (writer), ميزة كاتب (Feature Writer).

- A-Box contains assertions about individuals, specifying their class.

In total there are 230 concepts in our current book ontology.

To validate and check consistency of the constructed ontology we use Pellet Reasoner, which is considered to be one of the best OWL-DL reasoner [33]. Pellet Reasoner was used along with Protégé editor.

### B. Aspect-based sentiment analysis

According to Figure 1, the ABSA process consists of two steps: a preprocessing of each text review and an identification of aspect terms and their polarities.

#### 1) Preprocessing

Several treatments must be taken and multiple NLP techniques must be utilized, including sentence splitting, tokenization, normalization, Part Of Speech (POS) tagging and removing the stop words. Sentence splitting

Based on punctuation marks, each review is split into a set of distinct sentences. The review given in Table III, is split into two sentences.

#### Tokenization and normalization

The next step is tokenization; it is applied to split each sentence into a list of tokens (see example of Table IV-a). At this stage, normalization is performed to make all letters written in the same format which will help alleviate spelling variations (see example of Table IV-b), which will provide better recall rate. For example, the normalization of "أ" (hamza) is "ا" (aleph mad) and the normalization of "أ" (aleph with hamza ontop) is "ا" (alef).

#### Part Of Speech (POS) tagging:

The fourth step consists of assigning a grammatical category to the given word. It's commonly referred to as POS Tagging. Stanford Arabic part of speech tagger is used to tag the words. This information will help us identify aspect term and opinion words. To determine the aspect term, all the terms with noun category are extracted. As well, to identify the opinion words, all the terms with adjective and verb category are extracted.

#### Stop-words removal:

The Fifth step is responsible of removing stop words like (... "this" تلك , "that" هذا , "at" في , "Which" الذي , "From" من ), The list of Arabic Stop-words is used and we keep only valence shifter (e.g.. "not" ليس , "never" أبدا , "No" , etc.)

TABLE II. EXAMPLE OF SENTENCE SPLITTING

Before	After
<p>review روايه طويله جدا . مليئه بالاحداث والاشخاص و التفاصيل في رأي ان اسلوب ها الادبي ضعيف جدا و لكن ما يميزها هو صدق التجربه وواقعيتها review ("A very long story. Filled with events, people and details, in my opinion, her literary style is very weak, but what distinguishes it is the sincerity of the experience and its realism.")</p>	<p>Sentence 1: رواية طويلة جدا ("A very long novel") Sentence 2: مليئة بالأحداث والأشخاص والتفاصيل في رأي أن أسلوبها الأدبي ضعيف جدا ولكن ما يميزها هو صدق التجربة و واقعيتها ("Filled with events, people and details, in my opinion, her literary style is very weak, but what distinguishes it is the sincerity of the experience and its realism")</p>

TABLE III. EXAMPLE OF TOKENIZATION AND NORMALIZATION

SENTENCE	Tokenization	Normalization
<p>مليئة بالأحداث والأشخاص والتفاصيل في رأي أن أسلوبها الأدبي ضعيف جدا ولكن ما يميزها ("Filled with events, people and details, in my opinion, her literary style is very weak, but what distinguishes it is the sincerity of the experience and its realism")</p>	<p>مليئة، ب بالأحداث ،بوالأشخاص و ، التفاصيل، في، رأي، أن أسلوبها الأدبي، ضعيف، جدا، ولكن، ما، يميزها، هو، صدق، التجربة ،و ، filled, of, event, and, persons, , and, the details, at, opinion, that, , her , style, literary, weak, very, and, but, what, dis- tinguishes, it, he, truth, experience, and, realism</p>	<p>مليئه، ب بالاحداث ، والاشخاص و ، التفاصيل، في، رأي، ان ، اسلوبها الادبي، ضعيف، جدا، و ، لكن، ما، يميزها، هو، صدق ، التجربه ،و، واقعيتها،</p>

## 2) Aspect term extraction and polarity identification

### Aspect-term extraction:

Aspect is a term for which a sentiment is expressed. However, there are two possible cases; the term aspect can be explicitly expressed as well as implicitly. For example, in the phrase: كتاب ممتاز ("It's an excellent book"), the aspect term "كتاب (book)" is made explicit with a positive opinion term رائع ("excellent"). But, in the phrase "استمتعت بقرائتها حقاً" ("really, I enjoyed reading it"). The term aspect is not explicitly present, it is simply mentioned by the feminine pronoun ها ("it"), and we can then infer that the aspect term may be a story قصة. Here, the opinion word استمتعت ("enjoyed") implicitly refers to this aspect term. In this paper, the proposed approach will be applied only to aspect terms that are explicitly expressed. Words whose grammatical category corresponds to nouns (like NN: singular noun, NNP: proper singular noun) are considered to be candidates for being aspect terms. To determine this,

they are matched with the concepts of the domain ontology included in the T-Box of the book ontology. An explicit aspect term in the review corresponds to a concept present in the T-Box. For example in the review: "كتاب رائع" "It's an excellent book", the noun term "كتاب" "book" is compatible with the concept كتاب in T-Box and it is extracted as an aspect term. Aspect-term polarity identification:

For aspect-term polarity identification, sentiment shifters combined with A-Box are used to determine the polarity of the extracted opinion words in reviews. As mentioned in [35], sentiment shifters, are terms that can change opinion orientations". (Like: "ليس" "not", "أبداً", "never", "لم", "No", "لا", "will not", "لا", "No", "....."). When one of them appeared before the opinion word, it would change the polarity of the opinion terms, from positive to negative, and vice versa. ". For example, in the sentence "هذه الرواية لم تعجبني" "This novel did not interest me". The negator "لم" ("did not") reverses the valance of the sentiment word "تعجبني" ("interest

me”). By using the A-box, the proposed approach checks if each adjective or each verb is an opinion word, then identifies contextual sentiment shifters before recovering and identifying its polarity. If yes, the proposed approach reverses the polarity of the current opinion word. If no, our approach gets its polarity from A-Box. To identify contextual sentiment shifters, regular expressions are used to match sentiment shifters, which is a sequence of characters that forms a search pattern and is mainly used for string matching [36]. The pattern sequence is a very brief way to express what we are searching. For example, the regular expression `\b w*(لم ليس لا ما لن) ow w* \b` is used to match sentiment shifters appeared before the opinion word “ow”. When matching, the polarity change from positive to negative, or from negative to positive. The activity diagram of the proposed approach is shown in Figure 4.



Figure 4. Activity diagram of the proposed approach

#### 4. EXPERIMENT

To evaluate the proposed approach, we firstly present in this section, the data-set used along with its baseline experiments and then we describe the evaluation metrics.

##### A. Data-set

The data used in this research is taken from the Semantic Evaluation workshop 2014 on ABSA (SemEval-2014). HAAD, the first ABSA dataset for Arabic language, consists of 1513 books review in Arabic selected from the LABR dataset and annotated by humans with aspect terms and their polarities [11]. It is provided in three files (training file, test-gold file, and the test file), and it is equipped with

```
<sentence id="915">
<text>مميزة هذا الكتاب أن الأبطال هم عرب مثلنا</text>
<aspectTerms>
<aspectTerm term="الأبطال" polarity="positive" from="19" to="26"/>
<aspectTerm term="الكتاب" polarity="positive" from="9" to="15"/>
</aspectTerms>
<aspectCategories>
<aspectCategory category="المزاجية" polarity="positive"/>
</aspectCategories>
</sentence>
```

Figure 5. An example of Human Annotated Arabic Dataset of Book Reviews following SemEval-ABSA14 annotation guidelines

a tool for common evaluation technique. This tool yields us the possibility to compare our results with those of the Test-gold file by computing the same measures used in the baseline approach [10].

Figure 4 depicts an example of Human Annotated Arabic Dataset of Book Reviews following SemEval-ABSA14 annotation guidelines.

Table V as described in [10] summarizes the aspect terms distribution over the polarity class in both training and testing datasets.

##### B. Baseline Approach

The HAAD dataset is provided with a baseline evaluation for the four tasks discussed in section 2. In this work, only the baseline evaluation for the two first tasks is considered. it is explained as follows:

###### 1) T1: Aspect term extraction baseline:

if the tokens are listed in the human annotations list of aspect terms of the training dataset, the baseline tags them in the test dataset as aspect terms [10].

###### 2) T2: Aspect term polarity baseline:

the baseline checks if each aspect term “t” in the test sentence “s” has been seen in the training set. If yes, the baseline gets the “d” most similar sentences to “s”, and assigns to “t” the most frequent polarity in the “d” sentences. If not, assigns to “t” the most frequent polarity label in the training set [10]. To compute the distance between sentences “s” and “d”, the baseline approach used the Dice coefficient similarity measure.

##### C. Evaluation metrics

In order to evaluate aspect term extraction (T1), F-measure (F1) is used. F-measure is the harmonic mean of precision (P) and recall (R). Precision and recall are two evaluation metrics used to evaluate the approach performance.

$$F1 = \frac{2.P.R}{P + R} \tag{1}$$

$$P = \frac{TP}{TP + FP} \tag{2}$$

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



TABLE IV. SUMMARY OF ASPECT TERMS AND THEIR POLARITIES [10]

Dataset	Polarity Positive	Polarity Negative	Polarity Conflict	Polarity Neutral	Total
Train	1252	855	26	126	2259
Test	124	432	1	22	579
Overall Dataset	1376	1287	27	148	2838

With:

- TP: True Positive
- TN: True Negative
- FP: False Positive
- FN: False Negative

In order to evaluate aspect term polarity (T2), the accuracy (Acc) of the proposed approach is computed and compared with the baseline approach:

$$Acc = \frac{TN + TP}{TN + TP + FP + FN} \quad (4)$$

## 5. RESULTS AND DISCUSSION

### A. Results

As discussed in Section 3, the proposed approach was implemented for the two sub-tasks T1: Aspect-term extraction and T2: Aspect-term polarity identification. Experimentation results are shown in Tables VI, VII and VIII. The results are very promising and show the effectiveness of the proposed approach compared to the baseline approach.

### B. Discussion

For the two tasks: Aspect Term Extraction and Aspect Term polarity identification, results show that best results were obtained with the proposed approach. Table IX shows the accuracy and F-measure obtained by each approach for each task. As illustrated in Table IX; we can state the following findings:

- The proposed approach achieves the best performance for both sub-tasks.
- The proposed approach outperforms the baseline approach.
- Regarding task T1, a significant improvement in performance is observed in terms of F-measure by 19%, precision by 24% and recall by 14%.
- Regarding task T2, the accuracy is improved dramatically by 55%.

## 6. ERROR ANALYSIS

This section will discuss the proposed approach's shortcomings. We examined cases for which our system fails

to correctly identify aspect terms and polarities. The aim of this analysis is twofold: (i) we aim to capture open challenges in Arabic sentiment analysis; (ii) we try to explain potential causes for errors, which could allow us to improve our system in the future. In the following, we examine significant errors illustrated with examples.

### 1) Implicit aspect term problem:

Among error categories, there are errors due to the absence of explicit aspect term. When aspects are not mentioned literally in a review, they are called implicit aspects and, in that case, our system fails to identify them. See for instance the following review تعليق اکتفني بان اقول انني ما زلت اقرها من فتره لى فتره ("Comment only to say that I still read it from time to time"). For this review, our system fails to identify the aspect term الرواية ("novel"), because it is expressed implicitly.

### 2) Errors Caused by sarcastic sentences:

Another cause of misidentification is the use of figurative language to express sarcasm, as in: اللى عندو قلم وميرو يكتب مقال ويطيرو ("who has a pen and puzzling writes an article and fly") is annotated as (aspect term = "مقال" ("article"); polarity="negative"). Sarcasm leads to an error because our approach does not address such expression and as a result, our system was not able to properly identify aspect term polarity.

### 3) Errors Caused by Human Annotators:

We found some annotation errors made by human annotators regarding the aspect terms in the HAAD test dataset. For example, the expression يعجبني ("I like him ") in the review id="255"

لم يعجبني أبدا ("I never liked it") is incorrectly annotated as an aspect term whereas it is a polarity term and, the aspect term is expressed implicitly. We also identified some reviews that are not annotated by human annotators as in review id="1569" حاجة اقصة لكن الكتاب حلو جدا وأنا استمتعت بيه أوي ("As for the end, I do not understand this as it is nice and its relationship with the light of God is as if there is an imperfect need, but the book is very sweet and I enjoyed it."). Our system properly identifies the aspect term in this review, and its polarity; (aspect term = الكتاب ("book"); polarity="positive"). However, the system





TABLE V. EXPERIMENTAL RESULTS OF ASPECT TERM EXTRACTION

	Precision	Recall	F1
Our approach	0.4543689	0.4041451	0.4277879
Baseline approach [10]	0.209877	0.264249	0.233945

TABLE VI. EXPERIMENTAL RESULTS OF ASPECT TERM POLARITY IDENTIFICATION

Polarity	Precision	Recall	F1
negative	0.981	0.847	0.9091
neutral	1	0.6667	0.8
positive	0.5694	0.9318	0.7069

TABLE VII. ACCURACY OF ASPECT TERM POLARITY IDENTIFICATION

	Acc
Our approach	0.8547
Baseline approach [10]	0.297064

TABLE VIII. COMPARISON WITH THE BASELINE APPROACH

TASK	Baseline Approach [10]		Proposed approach	
	F1	Acc	F1	Acc
T1	0.233945		0.4277879	
T2		0.297064		0.8547

performance will be affected because aspect term and its polarity are absent in the test dataset.

- 4) Errors Caused by sentences with comparative opinions:

Some cases of misidentification include sentences with comparative opinions. Comparative opinions have different syntactic forms. It becomes difficult to identify aspect terms due to the presence of several candidate entities around the opinion word, in addition to the difficulty of identifying the polarity of the aspect terms. As the following example shows فرأت لغازي القصبي روايات وكتب أفضل من هذه الرواية ("I read Ghazi Algosaibi novels and books better than this novel") since our system does not address comparative opinions, it will be disturbed by such a limitation.

## 7. CONCLUSIONS AND FUTURE WORK

This work focuses on ABSA for the Arabic language, considering, particularly two ABSA tasks: Aspect Term Extraction and Aspect Term Polarity. The aspect extraction is the most important task in ABSA, which can be either implicit or explicit. We focus on explicit aspect terms extraction and their polarity. In this work, a semantic aspect-based sentiment analysis approach for Arabic reviews was proposed. This approach, utilizes the Description logics (DL) for the identification of opinion aspects and their polarity. The proposed approach was evaluated using HAAD

datasets (a reference dataset based on Semantic Evaluation 2014 workshop SemEval-2014: Task-4). The analysis of various categories of errors related to the HAAD datasets are performed and results of experiments showed that the proposed approach outperforms the baseline approach proposed [10] with an overall enhancement around 19% for T1 in terms of F-measure and 55% for T2 in terms of accuracy.

For future work, we will improve the proposed approach by studying the implicit aspect term extraction for example; in the sentence استمتعت بقراءتها حقا ("I really enjoyed reading it") there is no explicit mention of the aspect term, and detecting the polarity of ambiguous words for example; in the sentence قصة قصيرة ("A short story") is not clear if the word قصيرة ("short") expresses a positive or negative opinion. For this we plan to use the benefits of reasoning services of DL combined with the linguistic rules to deal with this kind of challenging expressions.

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