Evaluating Compositional Approaches for Focus and Sentiment Analysis

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Abstract. This paper summarizes the results of evaluating a compositional approach for Focus Analysis (FA) in Linguistics and Sentiment Analysis (SA) in Natural Language Processing (NLP). While quantitative evaluations of compositional and non-compositional approaches in SA exist in NLP, similar quantitative evaluations are very rare in FA in Linguistics that deal with linguistic expressions representing focus or emphasis such as "it was *John* who left". We fill this gap in research by arguing that compositional rules in SA also apply to FA because FA and SA are closely related meaning that SA is part of FA. Our compositional approach in SA exploits basic syntactic rules such as rules of modification, coordination, and negation represented in the formalism of Universal Dependencies (UDs) in English and applied to words representing sentiments from sentiment dictionaries. Some of the advantages of our compositional analysis method for SA in contrast to non-compositional analysis methods are interpretability and explainability. We test the accuracy of our compositional approach and compare it with a non-compositional approach VADER that uses simple heuristic rules to deal with negation, coordination and modification. In contrast to previous related work that evaluates compositionality in SA on long reviews, this study uses more appropriate datasets to evaluate compositionality. In addition, we generalize the results of compositional approaches in SA to compositional approaches in FA.

Keywords: Focus Analysis, Sentiment Analysis, Compositionality, Rule-based, Dictionary-based

1 Introduction

Focus has an important role in Natural Languages. It helps to disambiguate sentences and clarify the speaker's intent. By emphasizing a particular element

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in a sentence, speakers can guide listeners to the intended interpretation. For example, in the sentence "*John* left" or " It was *John* who left" the focus on "John" clarifies that it is John, not someone else, who left. This helps avoid misunderstandings and ensures the message is conveyed accurately. There are various theories in linguistics that address how focus interpretation is expressed or derived in natural languages, and these theories can be categorized based on their stance on compositionality. Below is an overview of some key theories, distinguished by whether they consider focus meaning to be derived compositionally or not:

– `Compositional theories` : Alternative Semantics [23, 4, 16], Structured Meanings [28, 17]
– `Non-Compositional theories` : Contextual Theories [22], Cognitive Theories [6, 18]

In a compositional analysis of focus, the meaning of a sentence with a focused element is built up systematically from the meanings of its parts [23, 4, 16]. This approach relies on formal rules that ensure each component of a sentence contributes to the overall meaning in a predictable manner [23, 4, 13, 7, 16] among others. Rooth's focus theory is a prime example of a compositional analysis. It posits that every sentence has two parallel interpretations:

– `Ordinary Interpretation` : The standard meaning of the sentence, e.g. John left.
– `Focus Interpretation` : A set of alternatives that highlight the focus: John left, Mary left, Peter left

Each of these interpretations are derived using compositional rules, e.g. combining the meaning of "John" with the meaning of "left" using syntactic rules to a more complex meaning represented as a sentence "John left". This ensures that the meanings are built up from the parts "John" and "left" consistently, handling the ordinary and focus interpretations, respectively.

In a non-compositional analysis, the meaning of a sentence like "John left" is not strictly derived from its parts "John" and "left". Instead, the interpretation of "*John* left" or " It was *John* who left" depends on contextual or pragmatic factors that are not systematically predictable from the components of the sentence alone. The focus is understood primarily through its pragmatic impact [22, 6, 18].

So far, this theoretical discussion between compositional and non-compositional approaches for FA has not been tested quantitatively and/or automatically on a large dataset in linguistics. Instead, the theoretical discussion is usually evaluated qualitatively based on a few sentences illustrating problems for the compositional or the non-compositional analysis method see [16] for an overview.

Our first goal in this paper is to fill this gap in linguistic research and to provide a way to test compositional and non-compositional approaches for FA empirically and automatically based on a larger dataset than a handful of picked sentences. To do this, we will use available datasets and experimental approaches from a related field to FA, namely Sentiment Analysis (SA) in Natural Language Processing (NLP). SA in NLP deals with the automatic prediction of the polarity orientation of a sentence or paragraph such as positive or negative. For instance, the sentence "Chocolate is tasty" is associated with a positive orientation or polarity due to the word "tasty". We argue that the projection of the polarity orientation of words like "tasty" to the sentence "Chocolate is tasty" is related to the compositional rules of how focus or emphasis projects to the sentence level as in "*John* left" or " It was *John* who left". This means that both projections (polarity and focus projection) are affected by the same syntactic rules such as coordination, modification, and negation see [23, 17, 4, 16] for syntactic rules of focus projection and see [27, 14] for polarity projection in SA). To adapt approaches from SA to FA, it is necessary to modify the evaluation methods usually used to evaluate compositional and non-compositional approaches in SA [27, 14], because the evaluation is usually based on the accuracy prediction of reviews expressing sentiments, which can be very long. Predicting long reviews correctly requires more than compositional rules of how polarity projects to the sentence level considering syntactic rules of negation, modification and coordination. Instead, predicting long reviews also requires knowledge about how discourse relations between sentences work or to what extent stylistic rules matter for accuracy of polarity prediction. The latter rules are syntax or grammar-independent. For instance, some sentences in a long review play a more important role in polarity prediction such as first or last sentences. These grammar-external factors represent a "noise" factor in the evaluation of compositionality based on syntactic or grammatical rules expressed within a sentence. It is thus important to find a dataset with relatively short reviews (ideally one sentence long) for the evaluation of compositionality.

Our contribution to this article is three-fold: 1) Find or create a dataset that targets compositionality and minimizes the influence of syntax-external factors, 2) Test compositional with non-compositional approaches on this dataset and 3) Generalize the results from SA to FA as both analyses are strongly related.

The article is structured as follows. Section 2 provides more theoretical details about compositional approaches of focus and sentiment analysis. Section 3 describes the modification of the previous compositional approach and a method for the data selection and Section 4 presents the results and discussion. Section 5 provides conclusion and section 6 provides limitations and future work.

2 Compositional Approaches to Focus and Sentiment Analysis

Rooth's [23] focus theory is a foundational framework in semantics that addresses how elements within a sentence can receive special emphasis, or focus, and how this affects their interpretation. According to Rooth, focus elements have two distinct semantic interpretations: a) Ordinary Interpretation (Ordinary Semantic Value): This is the conventional meaning of the sentence without any emphasis.

For example, in the sentence "*John* left," the ordinary interpretation is simply "John left." and b) Focus Interpretation (Focus Semantic Value): This captures the alternatives that could potentially replace the focused element within the sentence, reflecting the range of possible contrasts. In the same example, the focus interpretation might be the set John left, Mary left, Peter left, indicating that any of these individuals could have been the subject of the sentence. As one alternative is true, namely "John left", this leads to the inference that other alternatives are false. This explains why the focus marking on "John" often leads to the contrasting interpretation of the sentence ('It's John who left, not Mary or Peter'). Rooth's theory proposes that these two interpretations are computed in parallel. This dual interpretation framework allows for a nuanced understanding of how focus operates within a sentence, affecting both its meaning and its pragmatic use in discourse. In Rooth's [23] focus theory, the interaction between focus and negation is particularly relevant as focus influences the interpretation of negated statements. When a focused element appears within a negated sentence, the ordinary and focus interpretations interact to produce the meaning of the sentence and its alternatives. For example, in the sentence "*John* did not leave," the ordinary interpretation is straightforwardly "John did not leave." However, the focus interpretation considers a set of alternatives such as John did not leave, Mary did not leave, Peter did not leave. This interaction can lead to nuanced readings, such as emphasizing that it was John, and not someone else from the alternative set, who did not leave. Coordination plays an important role in FA too [23]. The coordination within the sentence with a focus element leads usually to a set of coordinated alternatives. The example "It was John and Mary who left" triggers the set of coordinated alternatives like John and Mary left, John and Peter left, Peter and Susan left, ... excluding non-coordinated alternatives like John left (by himself), Mary left (by herself), ... Rooth's framework ensures that both the negation, coordination, and the focus are properly accounted for in deriving the meaning, preventing unintended interpretations, and maintaining coherence with the contextual alternatives. As discussed in appendix 8.1, the formal details of FA are important for understanding the method.

Compositional approaches have been also implemented in SA such as [27, 14], which apply the principles of compositional semantics where the meaning of a sentence is derived from the meanings of its parts and the syntactic rules used to combine them. These approaches break down a review into sentences and each sentence into its syntactic components, represented as nodes in a tree structure. Each node captures a word, its context, and its syntactic dependencies, forming a hierarchical representation of the sentence's structure. The sentiment score is evaluated at each node based on the word and its context expressed in the corresponding node. This mirrors how human language processing works according to compositional analysis of Natural Languages (§Introduction), where the meaning of a phrase is understood by combining the meanings of individual words according to syntactic rules. The appendix 8.2 provides the formal details of SA.

The recursive traversal of each node in the hierarchical representation of a sentence allows compositional approaches to account for the context and syntactic dependencies that influence the polarity orientation of the sentence. Words in natural language often depend on their context to convey the correct sentiment. By analyzing the tree structure, compositional methods can effectively manage such dependencies. This ensures that each sentiment word's score is appropriately weighted and contextualized within the sentence.

Some of the advantages of a recursive and compositional approach of SA is that SA is comprehensive and explainable. By breaking down sentences into smaller, manageable parts and analyzing each part in its context, compositional approaches can aggregate individual word sentiments into a coherent overall score. This methods effectively capture the nuances and complexities of natural language, producing a more accurate and reliable sentiment analysis [8]. Some compositional analyses in SA exploit words expressing sentiments such as "tasty" from sentiment dictionaries and syntactic rules together with sentiment-shifting elements like negation and modification as in "This cholocate is not very tasty" [27, 14]. These approaches have used the formalism of Universal Dependencies (UD) which is a universal framework for the annotation of grammar across different human languages [29] in order to capture syntactic rules of polarity projection [27, 14]. The authors in [14] tested their analysis on the dataset provided by the Shared Task Rest-Mex 2023 organizers [2] and compared the results of their compositional analysis with a comparable dictionary-based non-compositional analysis of SA that use heuristic rules to address modification and negation such as VADER [10]. In addition, they compared their results with non-compositional and non-dictionary-based approaches based on Deep Learning methods. Their results have shown that their compositional approach is superior to VADER in the accuracy of polarity prediction of long reviews that can contain up to 20 sentences [14]. While previous compositional approaches like the one from [14] implemented negation and modification, they mostly ignored the relation between negation, coordination, and modification. In the next section, we show how we modify the code from [14] to include more complex sentences such as coordination and we discuss the appropriate datasets we used to evaluate compositionality by reducing sentence external factors that might influence the accuracy prediction.

3 Data and Methods

3.1 Code Modification

We suggest a modification of the code in [14] that does not account for complex sentences combined by coordination.

It specifically deals with the interaction between negation and coordination.

In the modified version of [14], coordination has the scope over the negation predicting the correct interpretation of conjoined sentences. For instance, in the sentence "No es muy costoso pero tiene una vista bonita" ("It is not very expensive but it has a beautiful view"), the negation word "no" inverts the negative sentiment of ”costoso,”, but not of the sentiment word ”bonita”, contributing to a more accurate overall sentiment score. The link to the modified version of the code is available under § Online Resources.

3.2 Dictionaries

We use the sentiment dictionary SO-CAL for English [5]. The content of this dictionary and its parameters are not modified or tuned. For comparison with the non-compositional method, we use the sentiment dictionary that is already built into the non-compositional approach [10].

3.3 Data

We use a dataset of 1744 hotel reviews in English from OpeNER [1]. It was extracted from different booking sites from November 2012 to November 2013. Each review is annotated with individual polarity expressions and their polarity (positive or negative) as demonstrated by a simple example such as ”My best honeymoon.” (Polarity: Positive) from [3]. The dataset has additional information such as polarity holders or agents, etc. [3], which we ignore. The mean count of sentences per review in the OpeNER dataset is 1.06. The mean count of tokens per sentence is 16.38, which means that the sentence approximately contains 16 words on average. This makes this dataset a good choice for our goal as we want to test how the polarity projects on the sentence level and reviews with several sentences pose an additional complication to this goal. Furthermore, we performed necessary prepossessing on the dataset to overcome data discrepancies, noise, and outliers to ensure the quality of discovered patterns as described in [11].

From this dataset, we only use reviews in English with at least one sentiment word as our goal is to test the compositionality or non-compositionality of SA (§ Introduction). We thus discard 350 reviews in English that do not contain any polarity expression at all, so our evaluation is conducted on the remaining reviews that do contain subjectivity. If the review is a complex sentence and contains more than one polarity expression, e.g. “This hotel is expensive, but the staff is nice”, it is assigned a list of polarity values associated with each polarity expression such as [negative, positive] [3]. Then, the aggregate polarity for the review as a whole is computed as the majority value in that list, or a third polarity (neutral) if there is no majority value (e.g. [negative, positive]) [12]. We thus have a task of predicting three polarity labels (neutral, positive, and negative) on this dataset [12].

Negation poses an additional problem to the polarity prediction and our goal is thus to test compositional and non-compositional approaches dealing with negation. This is why we created another dataset just containing sentences with negation such as ”Chocolate is not tasty”. For this, we extracted a subset dataset containing reviews with negative words like ”not” (see [12] for the negation words in English). We call the dataset that contains all reviews expressing subjectivity ”Data All” and the dataset with reviews containing negative words

"Data Negation". In addition, we create a subset of the data that contains coordination to test the modification of our code in § Code Modification. We label this dataset as "Data Coordination." We use accuracy as our evaluation metric.

4 Results and Discussion

4.1 Original vs. Modified Compositional Approach

Table 1 shows that there is an improvement of three percent accuracy between the original code from [14] and its modified version that captures coordination as presented in § Code Modification.

Table 1. Accuracy Results from Comparison between Original Code and Modified Code

Method	Dataset	Accuracy
Original version from [14]	Data Coordination	0.71
Modified version	Data Coordination	0.74

4.2 Compositional vs. Non-compositional Approaches

Table 2 shows a difference in accuracy of 9 percent between compositional and non-compositional approaches in the dataset containing all reviews (see compositional M. 0.80 vs. non-compos. M. 0.71). However, the distinction decreases with negative subjective statements (see compositional M. 0.72 vs. non-compositional M. 0.70).

Table 2. Accuracy Results from Comparison between Compositional and Non-Compositional Approaches

Method	Dataset	Accuracy
Compositional dictionary-based	Data Negation	0.72
Compositional dictionary-based	Data All	0.80
Non-Compositional dictionary-based	Data Negation	0.70
Non-Compositional dictionary-based	Data All	0.71

We also use a qualitative data analysis method, to compare the methods and their results. We subdivide the results into four conditions: false prediction by the compositional method, but correct prediction by the non-compositional method VADER (Condition 1). False prediction by both methods (Condition 2).

False prediction by VADER, but correct prediction by the compositional method (Condition 3). Correct prediction by both methods (Condition 4).

- `Condition 1` : "However, this does not make up for the expense and lack of space."
- `Condition 2` : "Room Tip : Best rooms are in another hotel, not there."
- `Condition 3` : "There was nothing that we did not like at this hotel."
- `Condition 4` :"It is worn down, not clean and the whole hotel looks like a mess."

Compositional approaches have issues with the scope of negation of certain semantic word classes that are considered propositional verbs like "make up" or "explain" that usually take a proposition or a sentence as their argument (see Cond. 1). In the example representing Cond.1, the arguments of the verb 'make up' are conjoined noun phrases "the expense" and "lack of space". However, their interpretation is a concealed proposition: "this does not make up for the expense and lack of space" means "this does not explain why the hotel is expensive and why there is a lack of space." Consequently, the negation does not scope over the sentence including nominal arguments, but over the main verb "make up". This case represents a mismatch between the syntactic structure that predicts the scope of negation over the clause including nominal arguments and semantic interpretation of the sentence where negation has scope over the main verb only. This is why our compositional approach does not correctly capture the polarity prediction of the sentence. Another problem is anaphoric and deictic expressions like "other", "here", etc. We see in the example representing Condition 2 that both methods have difficulties in capturing anaphoric and deictic references to targets of subjective statements (see Cond.2). In more recent approaches of SA, targets play an important role in polarity prediction [3]. Targets as well as other concepts need to be adapted to compositional approaches in the future. The non-compositional method has problems in predicting polarity if the negation does not show a close proximity to the sentiment word as in the example representing Condition 3. The dependency parser, however, correctly interprets the negative argument "nothing" as the object argument of the verb "like", thereby correctly predicting the scope of negation. The double negation in the example leads to a positive interpretation and hence to the positive polarity. The non-compositional approach seems to have trouble with non-proximal negative words and the correct interpretation of double negation in contrast to the compositional approach [27, 14]. Both methods (compositional and non-compositional) correctly predict the polarity of a sentence, whenever the scope of negation coincides with the linear order of the negation word as in "not clean" (see Cond.4). In the given example of Cond.4, the negation is close to the sentiment word "clean", hence the non-compositional approach can correctly predict the polarity of "not clean". Even though the compositional approach is independent of the linear order of negation, it correctly predicts the scope of negation in "not clean" as the negation word "not" is a modifier of the adjective "clean". Consequently, both approaches predict correctly the polarity orientation of the given example.

We have argued that Focus Analysis (FA) and Sentiment Analysis (SA) are strongly related, and the results from compositional approaches in SA based on sentiment datasets can be used as evaluation metrics for compositional approaches in FA. FA provides context and clarity about what or who is being discussed, while SA captures the emotional tone or attitude towards that focus. Their integration leads to a more accurate and nuanced understanding of texts, especially in complex cases involving multiple entities or topics. We have adjusted the head-child dependency relation using the English UD parser from [14] to control the scope of negation, coordination, and modification. Furthermore, we suggested using specific datasets that are better suited for evaluating compositional approaches in SA than previous evaluations that do not consider particular datasets, such as short reviews and data with negation.

We evaluated both approaches (our compositional approach and the non-compositional approach from VADER) by the accuracy of polarity prediction performed on two datasets (Data All and Data Negation). Our results show that the compositional method we adapted has much higher accuracy than the non-compositional approach of VADER on the dataset "Data All" and almost similar accuracy on the second dataset "Data Negation" (with only a two-percent difference). The lack of a big distinction between compositional and non-compositional approaches in the dataset "Data Negation" can be attributed to a relatively high match between the linear order of negation and the sentiment word, such as in "not clean," and the scope of negation in the dataset. This is confirmed by examples showing mismatches between the linear order of negation and the sentiment word and the scope of negation, as discussed in the qualitative data analysis. These analyses show better performance of compositional approaches whenever the negation is correctly parsed as a modifier by the UD parser, despite being distant from the sentiment word (see Cond.3). As such mismatches are relatively rare in our dataset, the improvement of the compositional approach does not stand out.

5 Conclusion

To conclude, compositional approaches show certain advantages compared to non-compositional approaches, but there are still issues to address in future research, such as the scope of negation, anaphoric and deictic expressions, and the integration of targets into polarity prediction. In our previous work, we demonstrated the extent to which polarity prediction of compositional approaches depends on the selection of dictionaries [15]. Most sentiment dictionaries ignore the issue of word ambiguity. For instance, the word old has a negative score in SO-CAL, but it can be used in contexts where it does not convey negative sentiment, such as "old tradition," "old friend," or "old town." Several approaches have addressed Word Sense Disambiguation (WSD), including WSD for lexicon-based approaches for SA [26, 25]. Even though the scope of our paper is not WSD but the evaluation of compositionality, WSD affects the evaluation of accuracy in polarity prediction of compositional approaches and, therefore, cannot be completely ignored. We will include the issue of WSD in future evaluations of compositional and non-compositional approaches. Additionally, a large dataset covering various focus expressions is necessary to ensure that a compositional approach can address all types of focus expressions, not just sentiment expressions.

6 Limitations and Future Work

We don't use any optimization or other task-specific adjustments in our experiments to try to increase the polarity prediction task's accuracy. This is because our primary goal in this study is not to increase the precision of the sentiment analysis, but instead to enhance Syntactic Parsing's temporal constraints so that it can benefit from its explainability and transparency compared to strictly supervised methods. Our method's use of a single English dataset to gauge accuracy in the polarity prediction task is another drawback. This is due to the fact that our method needs language-specific sentiment dictionaries in order to recognize polarity-shifting components like intensification and negation. In future, we will obtain these resources to test and evaluate our study in other languages too.

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8 Appendices

8.1 Formal details of FA

A key component of Rooth's focus theory is the focus operator $\sim$, which takes propositional scope over the entire sentence and integrates the focus interpretation with the context. The scope of the operator is represented in [$\sim$C] as follows: $\sim$ C[*John* left]. The operator $\sim$ "resets" the focus value to an ordinary value, ensuring that only the relevant alternatives are considered, thereby preventing an overload of uninterpreted alternatives (for modifications and extensions of this theory, see Beck 2006). Rooth's assumption that every sentence with a focus expression implies a (covert) focus operator at a certain level of representation, usually at the sentential level or scope, is shared by other linguists (see Jacobs 1984, Chierchia 2004).

Rooth assumes a compositional analysis of focus. Compositionality refers to how the meaning of a sentence is built up from the meanings of its parts, specifically addressing how focus affects this process. The compositionality is captured by the function application rule. According to Beck's (2006) extension of Rooth's focus analysis, the function application rule applies to both the ordinary and focus interpretations, which are derived in a parallel manner. The function application rule states that if X is a phrase composed of two parts Y and Z, then the interpretation of X under an assignment function g (which assigns values to variables) is the result of applying the interpretation of Y to the interpretation of Z under g.

Formally, this is represented as:

$$[[X]]_g = [[Y]]_g([[Z]]_g)$$

Additionally, when considering focus, another function h is introduced to handle the focus interpretation. Thus, the interpretation of X under both g and h is:

$$[[X]]_{g,h} = [[Y]]_{g,h}([[Z]]_{g,h})$$

To illustrate this with an example, consider the sentence "*John* left". The ordinary interpretation and focus interpretation are derived compositionally in parallel.

For the ordinary interpretation:

$$\begin{aligned} \text{left}_{g,h}(John, h) &= \lambda x.\text{left}(x)(John, h) = \text{left}(h(1)) \\ \text{left}_{g,h}(John, h) &= \lambda x.\text{left}(x)(\text{John}_{\text{Focus},g,h}) = \text{left}(h(1)) \end{aligned}$$

Here, $John_g$ is interpreted as the value assigned to *John* by the function g, and $left_g$ is the function that applies to this value, resulting in $left(g(1))$.

For the focus interpretation:

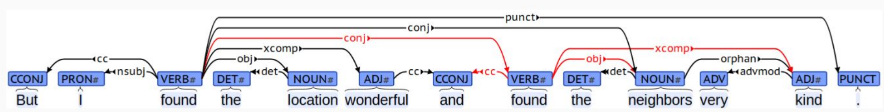
$$\begin{aligned} \text{left}_{g,h}(John, h) &= \lambda x.\text{left}(x)(John, h) \\ &= \text{left}(h(1)) \\ \text{left}_{g,h}(John, h) &= \lambda x.\text{left}(x)(\text{John}_{\text{Focus},g,h}) \\ &= \text{left}(h(1)) \end{aligned}$$

In this case, $John_{g,h}$ is interpreted according to the focus function h, and $left_g$ applies to this focused value, resulting in $left(h(1))$.

By maintaining separate functions g and h for ordinary and focus interpretations respectively, Beck (2006) ensures that both interpretations are systematically and compositionally derived, reflecting how focus elements influence the meaning of sentences within a context. This dual approach allows for a precise and structured handling of how focus affects interpretation, integrating Rooth's [23] insights into a formal semantic framework.

8.2 Formal details of SA

Following are formal details of some compositional approaches in SA. The authors in [14] suggest an adaptation of an unsupervised compositional and recursive approach in SA (Vilares et al., 2017 [27]) to the Universal Dependencies (UD) formalism [29], as it has since become the de facto standard for multilingual dependency parsing. Figure 1 shows a dependency structure for an English sentence and a CoNLL-U Format which represents word lines containing the annotation of a word/token with respect to various linguistic properties such as part of speech (POS), lemma, dependency relation of the word to its head, morphological features, etc. The dependency structure and linguistic properties of word/tokens as in CoNLL-U Format are an integral part of UD.




```
# sent_id = reviews-044427-0003
# text = But I found the location wonderful and the neighbors very kind.
1    But        but        CCONJ   CC   _                                          3   cc      _          _
2    I          I          PRON    PRP  Case=Nom|Number=Sing|Person=1|PronType=Prs  3   nsubj   _          _
3    found      find       VERB    VBD  Mood=Ind|Tense=Past|VerbForm=Fin           0   root    _          _
4    the        the        DET     DT   Definite=Def|PronType=Art                  5   det     _          _
5    location   location   NOUN    NN   Number=Sing                                3   obj     _          _
6    wonderful  wonderful  ADJ     JJ   Degree=Pos                                 3   xcomp   _          _
7    and        and        CCONJ   CC   _                                          6   cc      _          _
7.1  found      find       VERB    VBD  Mood=Ind|Tense=Past|VerbForm=Fin           _   _       3:conj     _
8    the        the        DET     DT   Definite=Def|PronType=Art                  9   det     _          _
9    neighbors  neighbor   NOUN    NNS  Number=Plur                                3   conj    7.1:obj    _
10   very       very       ADV     RB   _                                          11  advmod  _          _
11   kind       kind       ADJ     JJ   Degree=Pos                                 9   orphan  7.1:xcomp  SpaceAfter=No
12   .          .          PUNCT   .    _                                          3   punct   _          _
```

Fig. 1. UD formalism.(http://universaldependencies.org/eacl17tutorial/infrastructure.pdf).

The authors in [14]) used Stanza, which is a natural language toolkit based on UD-formalism that provides a basic analysis of the input text such as lemmatization, part-of-speech (POS) and dependency parsing (Peng Qi et al., 2020 [21]). The dependency parser is based on UD parser from Qi et al. 2018 [20]. To demonstrate the approach in [14], let's consider a Spanish example *No es excelente* 'It is not excellent' and the associated dictionary entries with token ids, text, lemma, POS ('upos'), morphological features ('feats'), head ids and dependency relations ('deprel'):

- `first word` : 'id': 1, 'text': 'no', 'lemma': 'no', 'upos': 'ADV', 'feats': 'Polarity=Neg', 'head': 3, 'deprel': 'advmod'
- `second word` : 'id': 2, 'text': 'es', 'lemma': 'ser', 'upos': 'AUX', 'feats': 'feats': 'Mood=Ind—...', 'head': 3, 'deprel': 'cop'
- `third word` : 'id': 3, 'text': 'excelente', 'lemma': 'excelente', 'upos': 'ADJ', 'feats': 'Number=Sing', 'head': 0, 'deprel': 'root'

Head ids and dependency relations play an important role as they provide information about the syntactic relation of words and the hierarchical structure of the sentence. Head ids contain information about parent-child relations. Take for instance, the negation word *no* and the copular word *es* in the previous example, which have *excelente* as their head. This means that the word *excelente* is the highest node and the children *no* and *es* are the lowest nodes in the structure. This head-child relation can be used to define the scope of negation. If the negation is a child of a sentiment word as its head, the polarity of the sentiment word needs to be shifted.

In order to be able to calculate the polarity score of a sentence, they perform several steps that can be described in a nutshell as follows:

- `Step 1` : Find sentiment words in the input text and assign polarity scores to the sentiment words
- `Step 2` : Create a dictionary of head ids and their correspondent children ids
- `Step 3` : Identify target words that influence the sentiment word such as negation
- `Step 4` : Calculate the polarity score for the input sentence

Let us illustrate these steps by looking at the given Spanish example. First, the authors identify the sentiment word *excelente* in the input text and add new entries to the dictionary associated with this word, namely the elementType: 'count' and the polarity score or 'elementScore': 5. They use the dictionaries by SO-CAL for Spanish [24], [27], in which the polarity score for sentiment words ranges from -5 (the most negative) to +5 (the most positive).

- `Sentence` : *No es excelente* 'It's not excellent'
- `Step 1` : label sentiment words
- **`dictionary of the sentiment word`** : 'id': 3, 'text': 'excelente', 'lemma': 'excelente', 'upos': 'ADJ', 'feats': 'Number=Sing', 'head': 0, 'deprel': 'root', 'elementType': 'count', 'elementScore': 5

Step 2 consists of creating a dictionary with head ids as keys and a list of children as a key value in order to find potential polarity shifters or target words such as negation and modification. Each key-value pair of this dictionary represents a head-child tree branch as represented in Figure 2.

In the UD-formalism, the head id 0 and its child represent the highest tree branch and the child of the head id 0 and its children represent the second highest branch. In the given example, the second-highest branch is also the lowest branch:

- `Sentence` : *No es excelente*
- `Step 2` : Create a dictionary with heads as keys and their correspondent children as values
- `head-child-dictionary` : 3: [1, 2], 0: [3]

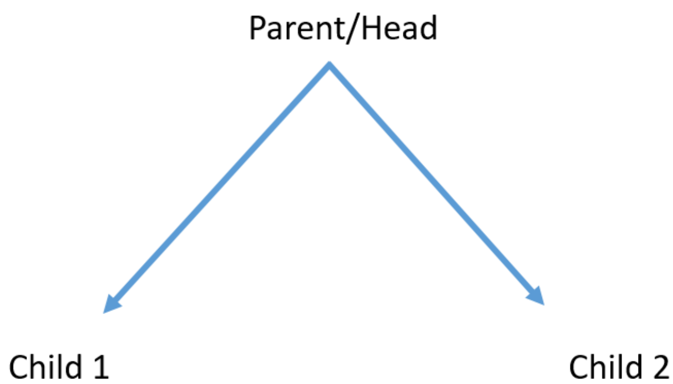


Fig. 2. Example of a head-child tree branch

Head-child branches represent an important unit in compositional approaches to FA and SA. In FA, the head represents the function in Functional Application (FA) applied to arguments of the sentence (see § Compositional approaches to Focus and Sentiment Analysis). In SA, head-child branches have been used to identify target words that can shift, weaken or strengthen the polarity of sentiment words [14].

Step 3 consists of identifying target words that can modify the sentiment word identified in step 1. To achieve this goal, the authors loop through branches upwards and check for a sentiment word, negation and/or modification in the same branch. For this, they calculate the order of branches from the lowest to the highest branch associated with a sentence. In the given sentence example *no es excelente*, the sentiment word and negation are in the same branch.

Step 4 consists of calculating the polarity score for each branch upwards by applying the formula for the calculation of the polarity score in (1) from Vilares et al. 2017 [27], where the variable a equals the elementScore of a sentiment word such as *excelente*, the variable b equals a value that depends on the strength of the intensifier such as *muy* taken from a list of intensifiers and negation has a score of -4 or +4 depending on the positive or negative value of a:

– `Step 4` : Calculate the polarity score for the branch *3: [1, 2]*

$$a * (1 + b) + (sign(a) * -4) = polarityscore \tag{1}$$

According to the formula in (1), the polarity score for the lowest branch 3:[1, 2] equals 1, if we calculate 5*(1+0)-4. As the highest branch simply expresses an identity relation between the root and the head of the previous branch, the polarity score remains the same, namely 1, and the calculation finishes with the highest branch. The authors take the polarity score of the highest branch ("top branch") to be the final result for the polarity calculation.

They also discuss an example with more branches in Figure 3.

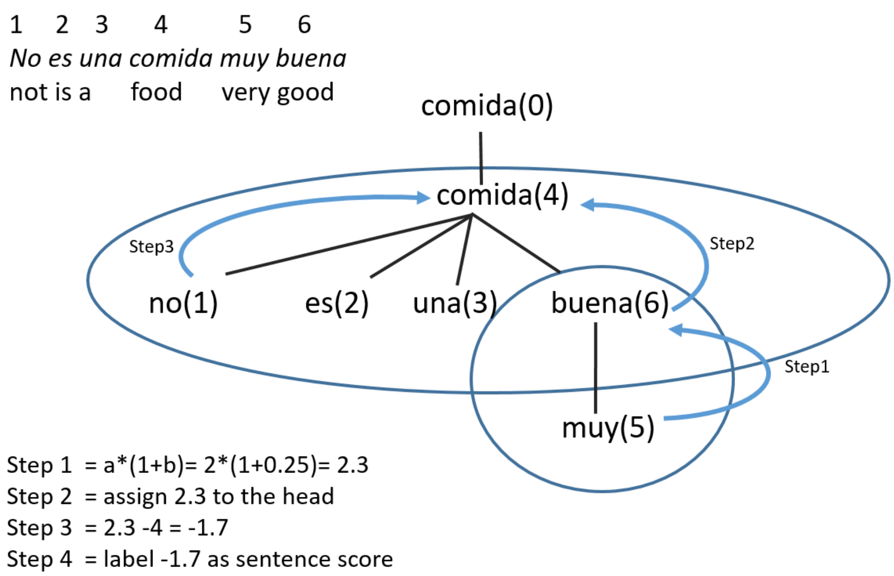


Fig. 3. Example with several branches

First, the intensification of the adjective *buena* 'good' is computed by the intensifier *muy* 'very'. The score of the intensifier *muy* is 0.25 [27]. The result for this calculation is 2*(1+0.25)=2.3. This score is assigned to the nominal head *comida* 'food' as the result of the nominal modification. Collecting information from the lowest branch and bringing it up to the highest branch (e.g. nominal phrase) is a common step in formal grammars such as Head-driven Phrase Structure Grammar (HPSG) [19] or Minimalist Grammar [9]. As the negation is a child of the nominal head with a polarity score 2.3, the negation has scope over the nominal head. As a result, the polarity score 2.3 is substracted -4 and the output of the calculation is -1.7.

The calculation finishes with the highest branch, which expresses an identity relation between the root and its child. The calculation steps are summarized as follows:

- `Sentence` : *No es una comida muy buena* 'It's not a very good food'
- `polarity score of the lowest branch` : 2 * (1 + 0.25) = 2.3
- `polarity score of the higher branch` : 2.3 -4 = -1.7
- `polarity score of the highest branch` : -1.7 (final polarity score)

9 Online Resources

The files used for the experiment and the updated code for the compositional SA are available on GitHub.

- GitHub