Advance Sustainable Science, Engineering and Technology (ASSET)
Vol. 5, No.1, April 2023, pp. 0230109-01 ~ 0230109-07
ISSN: 2715-4211 DOI: https://doi.org/10.26877/asset.v5i1/14897

Aspect-based Sentiment Analysis on Car Reviews Using SpaCy Dependency Parsing and VADER

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Abstract. All businesses, including car manufacturers, need to understand what aspects of their products are perceived as positive and negative based on user reviews so that they can make improvements for the negative aspects and maintain the already positive aspects of their products. One of the available tools for this task is Sentiment Analysis. The traditional document-level and sentence-level sentiment analysis will only classify each document / sentence into a class. This approach is incapable of finding the more fine-grained sentiment for a specific aspect of interest, for example, comfort, price, engine, paint, etc. Therefore, in this case, Aspect-based Sentiment Analysis is used. A total of 22.702 rows of car review data are scraped from the Edmunds website (www.edmunds.com) for a specific car manufacturer. Dependency Parsing and noun phrase extraction were carried out using the SpaCy module in Python, and VADER sentiment analysis was used to determine the polarity of the sentiment for each noun phrase. Results showed that the vast majority of the sentiments are on the positive aspects: comfortable to drive, good fuel economy / mileage, reliability, spaciousness, value for money, helpful rear camera, quiet ride, good acceleration, well-designed, good sound system, and solid build. The results for the negative aspects have some similar aspects with those in the positive class but has a very low frequency. This finding means that the vast majority of the users are satisfied with multiple aspects of the produced cars. The limitation of this research and future research direction are discussed.

Keywords: aspect-based sentiment analysis, car reviews, SpaCy Dependency Parsing, VADER

(Received 2023-03-07, Accepted 2023-04-25, Available Online by 2023-04-30)

1. Introduction

All businesses, including car manufacturers, need to understand what aspects of their products are perceived as good and bad based on user feedback so that they can improve the negative aspects and maintain the already positive aspects of their products [1]. This is part of the *kaizen* principle which in this case is related to continuous improvements of the products [2]. Sentiment Analysis (SA) is a part of the Natural Language Processing (NLP) task of extracting and analyzing people's opinions / perceptions toward certain entities such as products and services [3]–[5]. SA can be used to analyze the users' sentiment polarization (positive or negative) toward a product or service. SA can be divided into three levels: document-level SA, sentence-level SA, and aspect-based SA (ABSA) [6]. The traditional document-level and sentence-level sentiment analysis will only classify each document / sentence into a class. This approach is incapable of finding the more fine-grained sentiment for a specific aspect of interest, for example, the comfort, price, engine, paint, etc of a car. This is particularly trickier if the document / sentence contains mixed positive and negative sentiments such as "*The price is good but it's not comfortable to drive*". The traditional document-level sentiment analysis will miss such details and have difficulties in classifying the document into positive or negative sentiments. In this case, ABSA can identify the aspects of the product that are perceived as positive or negative by the users / customers. However ABSA is more difficult to perform since it has to identify a more fine-grained investigation [7]. ABSA had been used in Scientific Reviews [8], smart government app reviews [9], and tweets [10]. One of the data sources that can be used for SA / ABSA is based on review data that is available online [11], [12]. In this research, ABSA is applied to car review data to extract information on the positive and negative aspects of the cars produced by a certain car manufacturer.

The approaches used in ABSA are unsupervised methods [13]–[15], lexicon-based methods [16], [17], transfer learning [1], [18], [19], and deep-learning-based methods [20]–[22]. From those approaches, the three mainstream methods are lexicon-based, traditional machine learning, and deep learning methods [6]. This research will belong to the lexicon-based ABSA. The ABSA in this research will be facilitated by using a word dependency parser to identify phrase nouns and combined with a lexicon-based sentiment classifier called VADER (Valence Aware Dictionary and sEntiment Reasoner). The dependency parser is part of the SpaCy English pipeline which is a Python submodule for NLP. The SpaCy pipeline consists of multiple components such as Tokenizer, Part-Of-Speech (POS) tagger, Dependency Parser, Named-Entity Recognition, and Lemmatizer [23]. SpaCy is proven to be the fastest NLP parser available while also providing the best state-of-the-art accuracy [24]–[26]. In this research, the POS tagger and Dependency Parser components are mainly used to identify the phrase nouns that reflect the aspects of interest. The second part of the analysis, VADER, is a lexicon-based sentiment analysis tool that bases the sentiment classification on positive or negative keywords such as "great", "good", "worst", and "poor" [27]. Both SpaCy and VADER are available as Python modules/submodules.

2. Methods

The research methods are shown in Figure 1. The car review data are scraped from Edmunds website (https://www.edmunds.com) for one specific car manufacturer. The car review data consists of the review title and the content which are first concatenated before undergoing further analysis. These strings will then undergo dependency parsing and noun phrase extraction using the Language Processing Pipelines in the SpaCy [23] module in Python. The parser is a transition-based dependency parser. The pipeline used is the large English pipeline named "en_core_web_lg". This pipeline is trained using three datasets: OntoNotes Release 5.0 (University of Pennsylvania), ClearNLP (Emory University), and WordNet 3.0 (Princeton University) [23]. The accuracy for the Part-of-speech tagger component is 0.97, 0.92 for Sentence segmentation precision, and 0.90 for Labeled dependencies [23]. The extracted phrase nouns then will be classified into positive or negative sentiments using VADER SentimentIntensityAnalyzer [27] submodule in the nltk [28] module in Python. Lastly, frequency analysis is applied to the phrase nouns for each sentiment class to extract the aspect-based sentiment and the result is interpreted. All of the analyses were done using Python 3.7 and Jupyter Notebook [29].

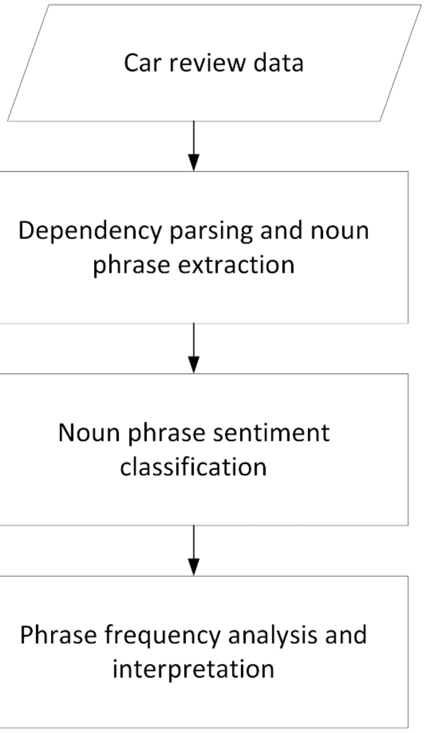


Figure 1. Research Methodology

3. Results and Discussion

A total of 22.702 rows of car review data are scraped from Edmunds website. Each review consists of a review title and review content. The length of the reviews is up to 5000 characters with an average of 412 characters which translates to up to 969 words with an average of 92 words. An example of dependency parsing and noun phrase extraction is shown in Table 1. The visualization is facilitated by using SpaCy visualization tools called displaCy.

A total of 123,372 noun phrases were extracted, which 112,620 of them (91.3%) were classified into positive sentiment. There are 52,956 unique phrases in the positive sentiment class and 6,443 unique phrases in the negative sentiment class. The frequency for each phrase was counted, and only phrases having a minimum of 20 counts in the positive sentiment class and 14 in the negative class are used in the next analysis. The threshold is set lower for the negative class to accommodate the inclusion of more phrases in the negative class because they have a far lower frequency than the positive class. The frequency of each phrase was then processed in the following manners:

- general or non-informative phrases such as “great car” are excluded;
- similar phrases, such as “reliable car” and “reliable vehicle”, are merged; and
- neutral sentiment or invalid phrases such as “front brake pads” are excluded.

The results for positive and negative aspects are shown in Table 2 and Table 3 respectively. Table 2 showed that the vast majority of the findings are on the positive side: comfortable to drive, good fuel economy / mileage, reliability, spaciousness, value for money, rear camera, quiet ride, good acceleration, well-designed, good sound system, and solid built. The top four positive sentiments which have significantly higher frequency highlight the aspects that many people perceived as positive and can be seen as the brand’s advantages compared to other brands i.e: comfortable to drive, good fuel economy / mileage, reliability, and spaciousness. On the other hand, Table 3 showed the results for the negative aspects such as low mileage, poor quality, poor design, hard to drive, and hard acceleration. However, this result in the negative aspects is contradicting some of the results in the positive aspect and only has a very low frequency. This contradictory result might arise due to different perspective and experience the users have or that they may compare the car they reviewed to other cars they had previously driven (whether from the same manufacturer or not). Overall, this finding means that the vast majority of the users are satisfied with multiple aspects of the produced cars.

The phrase frequency of the result might seem low compared to the number of the dataset because not all users will use phrase nouns in their reviews. Users may also use various wordings when expressing the same ideas, for example, users may write “roomy car” or “more leg room” to express the spaciousness of the car. These variations will cause the phrases to have low frequency and therefore get excluded from the analysis based on the aforementioned threshold.

The limitation of this study is that the pipeline is unable to extract sentiment information when no clear noun phrases are present, such as in the following sentences: “*Gas mileage exceptional. The back seat had a limousine feel to it. Never had a problem with it. Because of the safety issue with the accelerator we sold it.”*. Future research may enhance the phrase noun / aspect sentiment extraction by using a sentence-level or clause-level context understanding to extract richer informative aspects from the review data. Future research may also combine ABSA with Latent Dirichlet Allocation (LDA) to automatically identify the clusters of aspects [30], [31].

Table 1. Example of dependency parsing and noun phrase extraction

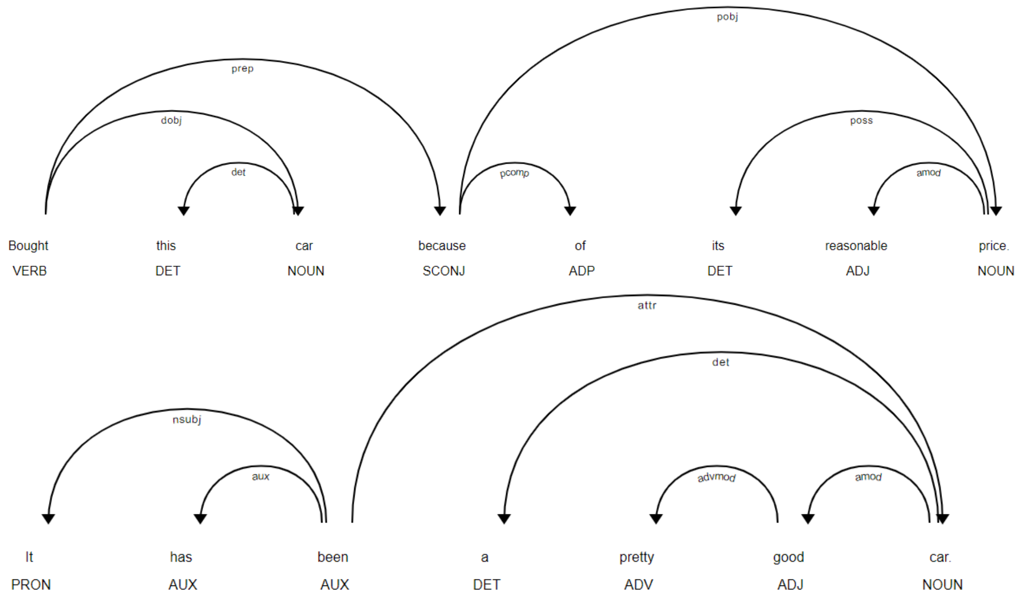
Phase	Example
Review text	Bought this car because of its reasonable price. It has been a pretty good car.
Dependency parsing	
Extracted noun phrases	‘reasonable price’, ‘pretty good car’

Table 2. The list of positive aspects and their frequency

Positive aspects	Frequency
Comfortable to drive	1248
Good fuel economy / mileage	721
Reliability	610
Spaciousness	498
Value for money	191
Rear camera	165
Quiet ride	128
Good acceleration	80
Well designed	73
Sound system	41
Solid build	23

Table 3. The list of negative aspects and their frequency

Negative aspects	Frequency
Low mileage	37
Poor quality	33
Poor design	27
Hard to drive	26
Hard acceleration	18

4. Conclusion

This research aims to perform aspect-based sentiment analysis on car review data to extract positive and negative aspects of car products from a specific car manufacturer. Results showed that the vast majority of the findings are on the positive aspects: comfortable to drive, good fuel economy / mileage, reliability, spaciousness, value for money, helpful rear camera, quiet ride, good acceleration, well-designed, good sound system, and solid build. The results for the negative aspects are low mileage, poor quality, poor design, hard to drive, and hard acceleration. However, the result in the negative aspects is contradicting the results in the positive aspect and only has a very low frequency. This finding means that the vast majority of the users are satisfied with multiple aspects of the produced cars. Future research can improve the identification of aspect-related sentiment when no explicit noun phrase is present in the reviews. Future research may also combine ABSA with LDA to automatically identify the clusters of aspects.

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