# Aspect Based Sentiment Analysis on Online Review Data to Predict Corporate Reputation

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Abstract: Corporate reputation is an intangible resource that is closely tied to an organization's success but measuring it and to derive actions that can improve the reputations can be a long and expensive journey for an organization. In the available literature, corporate reputation is primarily measured through surveys, which can be time and cost intensive. This paper uses online reviews on the web as the source for a machine-learning driven aspect-based sentiment analysis that can enable organizations to evaluate their corporate reputation on a fine-grained level. The analysis is done unsupervised without organizations needing to manually label datasets. Using the insights generated through the analysis, on one hand, organizations can save costs and time to measure corporate reputation, and, on the other hand, it provides an in-depth analysis that splits the overall reputation into multiple aspects, with which organizations can identify weaknesses and in turn improve their corporate reputation. Therefore, this research is relevant for organizations aiming to understand and improve their corporate reputation to achieve success, for example, in form of financial performance, or for organizations that help and consult other organizations on their journeys to increased success. Our approach is validated, evaluated and illustrated with Trustpilot review data.

## 1 INTRODUCTION

One of the major objectives of strategic business management is understanding driving factors of organizational performance (Crook et al., 2008). A possibility to evaluate and understand the heterogeneity of firms is the resource based view, that analyzes organizational resources and capabilities (Eloranta & Turunen, 2015). Those resources can be tangible or intangible (Kamasak, 2017) and according to researchers (Kor & Mesko, 2013; Molloy & Barney, 2015) intangible resources are considered as the most likely sources to an organizations success. Resources need to be valuable, rare, inimitable and not substitutable (Y. Lin & Wu, 2014). As such, according to Brahim & Arab (2011) intangible resources are most difficult to imitate and substitute and it can be argued, that these are the most valuable and rarest.

A main intangible resource of an organization that is increasingly receiving attention is corporate reputation (Wepener & Boshoff, 2015). According to Schwaiger et al. (2011) corporate reputation is "the ultimate determinant of competitiveness". However, measuring corporate reputation is a challenge for researches and businesses alike. Corporate reputation is seen as a factor that can explain the performance of a business, with Firestein (2006) arguing that corporate reputation is the strongest aspect of a company's sustainability. The relevance of corporate reputation has been stated numerously throughout the years, as such Abratt & Kleyn (2012) concluded that corporate reputation is a strategic resource to create competitive advantage. Furthermore, Vig et al. (2017) argue that corporate reputation can be a significant factor to predict financial performance. A reason for the possible correlation of corporate reputation and financial performance can be the effect of corporate reputation on the customers and its purchase intention. Keh & Xie (2009) observed a relation between corporate reputation and customer trust, that leads to increased purchase intention and willingness to pay.

The positive effect corporate reputation can have on a customer is becoming increasingly relevant in an environment where businesses need to become more customer centric for long term business success and profitability (Roy & Shekhar, 2010), making the corporate reputation more important than ever. As such, it can be said that understanding and improving

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corporate reputation is an essential part for an organization's success, but measuring it is a challenge for organizations.

A method to measure and evaluate corporate reputation is doing surveys, which is used by several researchers (Cintamür & Yüksel, 2018; Fombrun et al., 2015; Puncheva-Michelotti & Michelotti, 2010; Sequeira et al., 2015; Wepener & Boshoff, 2015) to measure corporate reputation. It can be argued that in order to receive the most reliable results possible, more data is needed and albeit the method of conducting surveys allows for targeted and in depth information, it can be time consuming when trying to collect as much data as possible. Furthermore, the relation between time and cost of a project (Babu & Suresh, 1996) can lead to higher cost involved with more time spent on conducting the survey. Therefore, it can be said that the main problem of organizations for evaluating and measuring corporate reputation, which is said to impact an organization's success, is the time and cost intensive methodology of collecting primary data through surveys. As such, a goal of an organization is to find a time and cost efficient way of measuring corporate reputation that can provide them added value.

To find an efficient way to tackle this problem, digital aspects should be highlighted, as according to Deloitte (2013), especially in the digital age, customers are increasingly more using digital touchpoints to resolve issues or get in contact with businesses. Dang & Pham (2020) further stress this relevancy by concluding that focusing on customers online is an essential part for businesses. As such, with the goal of finding a time and cost efficient way to evaluate corporate reputation and the increasing relevance of online aspects, another source to evaluate and improve corporate reputation is online reviews, where customers leave information such as feedback, positive or negative, recommendations or other valuable insights. According to Mayzlin et al. (2014), user generated online reviews are an important resource for consumers in their purchase decision. The main advantage of analyzing online reviews compared to conducting surveys is, that the reviews are already available online and no time and cost intensive surveys need to be carried out to collect the data. Furthermore, it can be argued that online reviews can offer more data than surveys, as there might be more customers that leave a review than customers who are ready to fill out a survey. It can be said that online reviews are a favorable way of measuring corporate reputation, but the questions of how they are analyzed needs to be answered as well.

To derive corporate reputation Chung et al. (2019) used sentiment polarity analysis on social media tweets about several companies. It can be argued that a tweet about a company is the same as an online review about a company. However, the main problem of sentiment polarity or sentiment analysis is that these analyses are done on an overall level and are not in depth enough to conclude concrete recommendations. As such, even when an organization is perceived overall positively there can be aspects of the organization that are seen as negatively that need to be improved. To tackle this problem, Chung et al. (2019) suggest that their main limitation, of their analysis not being in depth enough, can be addressed by ABSA, which can predict the sentiment of various aspects. The need and relevancy of ABSA is also backed up by Jebbara & Cimiano (2016), who argue that sentiment analysis needs to be done on a more fine-grained level and stress the importance of analyzing online reviews. The authors propose an ABSA that can extract sentiments expressed towards aspects from the text and thus, can detect multiple opinions in a single review. However, ABSA faces another time related problem, which is the manual labeling, research that has provided great ABSA results (Araque et al., 2017; Chen et al., 2017) needed a significant amount of time for manually labelling data. This will also limit the amount of data, as there is only a limited amount of data a human can label in a short time. As such, conducting ABSA on online reviews is a way to evaluate corporate reputation cost and time efficiently for an organization, but it needs to be done in a way that does not need manual labeling.

In the following sections, we describe relevant conceptual models, give details in our processing methodology, and conclude our work.

## 2 THEORETICAL FRAMEWORK

This section is intended to give an overview of the current state of research that is needed to understand corporate reputation.

### 2.1 Current State of Corporate Branding

To understand corporate reputation, the origin needs to be examined first. Corporate reputation is part of corporate branding, which can be described as a multidisciplinary field that has proved its usefulness in scientific and business environments (Biraghi & Gambetti, 2015). Corporate branding is currently experiencing three major shifts: (1) Brand strategy shifting its focus from products to an organizational perspective (Balmer, 2001); (2) Shifting from marketing to corporate strategy (Abratt & Kleyn, 2012); (3) Focusing on a stakeholder-centric view where the corporate brand is in an ongoing dialogue with the stakeholders (Melewar et al., 2012).

According to Melewar et al. (2012) the third shift is to move away from the traditional perspective and to incorporate a dynamic view on corporate branding. In this paper and for corporate reputation, the third shift is most relevant. Here, corporate branding is seen as an collaborative, relational and social process between the company and its stakeholders (Cornelissen et al., 2012). Melewar et al. (2012) further stress the fact that this view of corporate branding sees the brand as a vehicle that helps with the interaction between the company and its environment. Koporcic & Halinen (2018) assume that corporate brands are formed in the minds of the individual people and that the image is constantly being refined and changed. According to the authors, the key concepts that are part of corporate branding are corporate identity and corporate reputation. According to Podnar (2015, p. 29) corporate identity characteristics are real and constant attributes, whereas corporate reputation can be different, depending on the view of the observer.

## 2.2 Current Research and Definition on Corporate Reputation

Research has underpinned the relevance of corporate reputation and it is seen as a strategic resource to create competitive advantage (Abratt & Kleyn, 2012). Early on, corporate reputation was defined as a concept, that is a personal impression of the perceived entity (Shee & Abratt, 1989). In more recent researches on corporate reputation, Agarwal et al. (2015) affirm the view that corporate reputation is an unobservable construct that only exists in the minds of the stakeholders.

Definitions of corporate reputation can be found in a growing body of literature. There is currently no singular definition or adaptation of corporate reputation and some interpretations overlap or contradict. Table 1 displays several definitions of corporate reputation before deriving the main definition that will be used in this paper.

What is consistent throughout the definitions is that corporate reputation is a perception of an organization that a stakeholder has, that is based on past impressions. As such, this paper's definition of corporate reputation is:

*"A sociocognitive construct consisting of the organization's perception that a stakeholder has, that is built through past impressions"*

Table 1: Definitions of corporate reputation.

| Literature | Definition |
|---|---|
| Gotsi & Wilson, 2001 | Stakeholder's overall evaluation of a company based on experiences, communication and symbols that provide information about company's action, over time. The evaluation is also compared with rivals. |
| Chun, 2005 | Umbrella referring to the cumulative impressions of the different stakeholders of what the organization stands for and what it is associated with. |
| Barnett et al., 2006 | Collective judgement of observers of a corporation, based on assessments of financial, social and environmental impacts, over time. |
| Walker, 2010 | Relatively stable, issue specific representation of a company's past actions and future prospects compared to the standard. Takes time to build and can remain stable once built. |
| Rindova et al., 2010 | Sociocognitive construct that is characterized by quality and prominence to determine value as an intangible asset contributing to competitive advantage. |
| Lange et al., 2011 | Objective reality for the organization that is subjectively created by outside observers. |

The goal of this paper is to measure corporate reputation and several researchers have tried to measure corporate reputation and find relevant dimensions. Table 2 shows the proposed variables of researchers to measure corporate reputation.

Table 2: Dimensions of corporate reputation.

| Literature | Dimensions | Methodology |
|---|---|---|
| Wepener & Boshoff, 2015 | Emotional appeal, social engagement, corporate performance, good employer, service points | Online survey |
| Cintamür & Yüksel, 2018 | Financial performance, customer orientation, social and environmental responsibility, trust | Face-to-face survey |
| Fombrun et al., 2015 | Products, innovation, workplace, governance, citizenship, leadership, performance | Survey |
| Puncheva-Michelotti & Michelotti, 2010 | Management excellence, social responsibility, customer value, economic performance, patriotic appeal, consumer impact, emotional appeal, credibility | Survey |
| Sequeira et al., 2015 | Enterprise agreeableness, competence, commitment, ruthlessness | Survey |

The problem of these dimensions is that they are intended to be used through surveys and not ABSA on online reviews. As such, emotional appeal, management excellence, social responsibility and other dimensions are not applicable to this research where online reviews serve as the source of the analysis. Those dimensions are more applicable to surveys where detailed and targeted questions can be formed, however online reviews are based on what customers freely write. Therefore, it can be expected that those detailed and specific information cannot be found in online reviews, thus, most dimensions are not applicable to the nature of this research.

This paper's dimensions of corporate reputation will be based on Fombrum et al. (2015), due to the detailed explanations of the dimensions and attributes such as quality or value that can be more applicable to online reviews than the other dimensions shown in Table 2. Furthermore, Fombrum et al. (2015) propose two approaches for measuring corporate reputation, thus there is a better option of validating the results by comparing the results of dimensions 1 and 2; see Figure 1. It can be compared with a recent framework proposed by Wepener & Boshoff (2015). The frameworks have similarities such as performance or employee dimensions. However, the framework of this paper has a two-way approach to measure corporate reputation. Furthermore, the framework for this paper has more dimensions/attributes to measure corporate reputation on. This fact can be a bigger advantage when using online reviews as compared to surveys. In surveys, it can be said that the respondent can lose attention and motivation when the survey is longer, however when analyzing online reviews, this hurdle is not given, and a more extensive approach can be chosen. By having a framework to measure corporate reputation on, this can be applied onto ABSA. Where each dimension and attribute are an aspect that gets analyzed on its corresponding sentiment. This approach can be seen as an extension to current literature and research (Caviggioli et al., 2020; Chung et al., 2019) where corporate reputation is increasingly more often measured through social media or online reviews. However, those researchers have not applied their analysis on frameworks such as the proposed one of this paper. As such, this paper aims to conduct ABSA on a theoretical framework that is usually applied in surveys. This can lead to a more reliable result of corporate reputation that is backed up by a theoretical framework.

However, it can be seen that the dimensions of the proposed framework are diverse in their nature, some have a customer orientation, such as "products" whereas others have an employee orientation such as

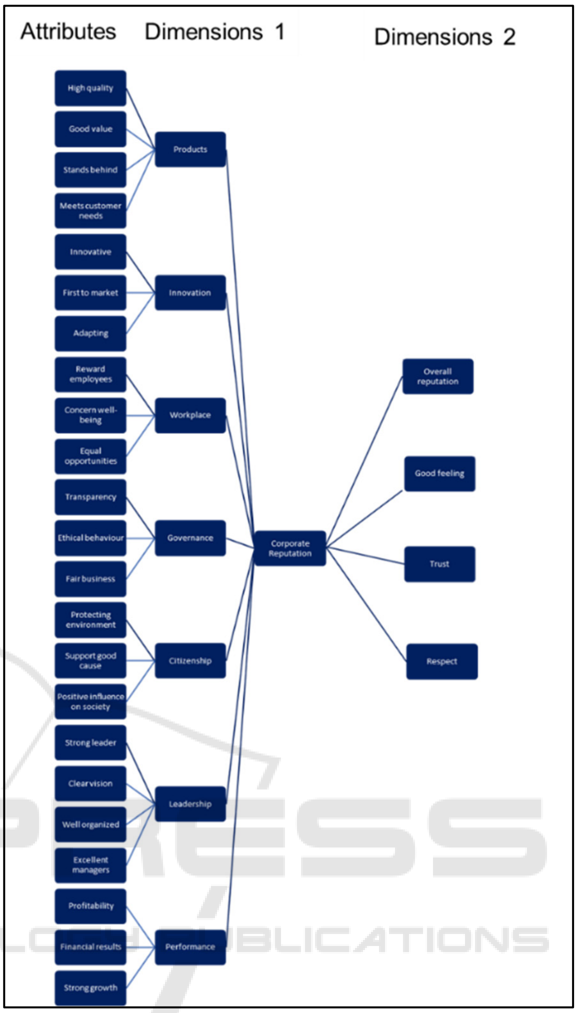


Figure 1: Framework of corporate reputation used in this paper.

"workplace". With online reviews being the source of the analysis, it can be argued that a singular online review source such as Trustpilot won't provide reviews that can cover all of the dimensions. However, the preliminary results have shown that all dimensions are covered and mentioned in reviews, albeit to a varying degree from the online review source Trustpilot (more in section 3.2). As such, all dimensions of Fombrum et al. (2015) are kept in the analysis, because having more aspects to analyze won't negatively affect the results and even less likely to be mentioned dimensions are kept in to provide a full picture. Furthermore, the attributes and dimensions of the framework were adapted to the customer language of online reviews and how a customer would write these terms in a review. E.g. "value" was translated to "price" as this word can be seen as more likely to be used in a review or "Equal opportunities” changed to “equality”. This was done based on the definitions Fombrum et al. (2015) provided.

According to Fombrum et al. (2015), corporate reputation can be measured through the extensive approach of measuring all attributes related to the dimensions of “dimensions 1”. However, corporate reputation can also be measured alongside the dimensions of “dimensions 2”. To evaluate validity of the models, the result of each dimension of “dimensions 1” was compared to the overall result of each dimension. Furthermore, the overall results of “dimensions 2” was compared to the overall result of “dimensions 1”.

It can be concluded that corporate reputation and identity both stem from corporate branding, with the identity being a real and constant construct whereas reputation is subjective and depends on the view of the observer. To measure this view of corporate reputation, it will be measured alongside the 34 attributes and dimensions of this paper’s framework (see Figure 1).

# 3 METHODOLOGY

This research is focusing on a mixed-method research as described by Saunders et al. (2015), which will be explained in the following.

## 3.1 Primary Research

For this paper, online reviews needed to be collected that can be analyzed in the later stages using a machine learning model that conducts ABSA. Karalevicius et al. (2018) who carried out sentiment analysis tackled the primary research by using a scraper that can collect social media and online review data. For this research, a Python scraper from CMI HVA was provided in order to collect the data. For a platform to scrape the reviews from and to analyze using sentiment analysis Vankka et al. (2019) opted for Trustpilot, because of the accumulation of companies with their respective reviews. As such Trustpilot was chosen for scraping the online reviews from. Finally, for this paper, the companies to extract the reviews from and to conduct ABSA on are Nike and Adidas, which amounts to over 2.000 scraped online reviews. Those companies are chosen, because they are prominent direct competitors and this allows to compare the results of the analysis and derive conclusions, which can also be relevant for organizations that want to use the proposed work to compare with their competition. Furthermore, these companies have both a balanced amount of positive and negative reviews, which allows to detect weaknesses, where reviewers are unsatisfied and clear improvement points can be deduced.

| title | text | stars |
|---|---|---|
| Good quality stuff | Good quality stuff, delivery took a little longer than usual, but that's to be expected at the moment. Trainers were not exactly as described on the website, so not sure if I will keep them. No issues with the rest of the order. | <div class="star-rating star-rating--medium">\n <img src="//cdn.trustpilot.net/brand-assets/4.1.0/stars/stars-4.svg" alt="4 stars: Great">\n</div> |
| Not worth the 1 star | Not worth the 1 star. You can't even contact them. | <div class="star-rating star-rating--medium">\n <img src="//cdn.trustpilot.net/brand-assets/4.1.0/stars/stars-1.svg" alt="1 star: Bad">\n</div> |
| Very good | Very good, but what on earth happened to my last order? I placed an order for a pair of Stan smiths, nothing special, and they took 4 weeks to arrive. I will blame the postal service since no other time anything like this has happened, but very weird | <div class="star-rating star-rating--medium">\n <img src="//cdn.trustpilot.net/brand-assets/4.1.0/stars/stars-5.svg" alt="5 stars: Excellent">\n</div> |

Figure 2: Starting dataset.

## 3.2 Secondary Research

Following the scraping of the review data, the online reviews were analyzed using secondary research. All the analyses were conducted using Python. The process is according to de Kok et al. (2018) who conduct ABSA and follow the same steps, with the exception that they used a pre annotated dataset where the aspects where defined in the dataset, for this paper, the additional step of aspect term extraction has to be added. De Kok et al. (2018) used readily available restaurant review data that they did not have to scrape and conducted ABSA on this data. With their result they could evaluate which aspect (e.g. food, ambience, service) the reviewee is mentioning and if they have a positive or negative sentiment towards the aspect.

| text | stars | textclean |
|---|---|---|
| Good quality stuff Good quality stuff, delivery took a little longer than usual, but that's to be expected at the moment. Trainers were not exactly as described on the website, so not sure if I will keep them. No issues with the rest of the order. | 4 | good quality stuff good quality stuff delivery took little longer usual thats expected moment trainer exactly described website sure keep issue rest order |
| Not worth the 1 star Not worth the 1 star. You can't even contact them. | 1 | worth star worth star cant even contact |
| Very good Very good, but what on earth happened to my last order? I placed an order for a pair of Stan smiths, nothing special, and they took 4 weeks to arrive. I will blame the postal service since no other time anything like this has happened, but very weird | 5 | good good earth happened last order placed order pair stan smith nothing special took week arrive blame postal service since time anything like happened weird |

Figure 3: Cleaned dataset.

<u>1 Cleaning Data:</u>

First the dataset was loaded; Figure 2 shows a snapshot.

In the following step, the column “stars” was stripped of all unnecessary characters until only the number of stars awarded by the reviewer was left. Then, the columns title and text were combined and these reviews were cleaned and lemmatized using NLTK, which is also according to de Kok et al. (2018). NLTK is one of the most popular and widely used libraries in the field of natural language processing (NLP), because of its simplicity and effectiveness (Hardeniya, 2015, p. 3). The end result is a dataset with a text that was stripped of all non-letters, words with not much value such as “the” and the number of stars awarded (Figure 3).

2 Aspect Term Extraction:

```
#Testing the dependency relations
txt = 'The laptop is great'
doc = nlp(txt)
spacy.displacy.render(doc,style='dep',jupyter=True)
```

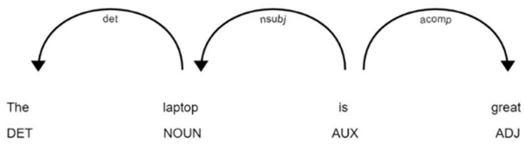


Figure 4: Example dependency parsing.

In this part, only the aspects were extracted. This is an extra step that de Kok et al. (2018) did not go through as their dataset was pre labeled, thus the aspects were already extracted beforehand. For example, in a review such as “The delivery went smooth” the aspect is delivery. These aspects need to be extracted to assign them the corresponding sentiment at the later stages. This was done using the dependency parser spaCy (Figure 4), which is regarded as the industrial strength natural language processing (Srinivasa-Desikan, 2018, p. 33) and researchers such as Bandhakavi et al. (2018) rely on spaCy for aspect extraction. Poria et al. (2016) propose a deep convolutional neural network, however supervised models are not fitting for this paper, because manually labelling the dataset is too time costly.

Using spaCy it is possible to extract the aspect and the corresponding sentiment, which is mostly an adjective. Figure 5 illustrates how the aspects are extracted.

Even though spaCy is an often used and efficient way of extracting aspects, the major downside is that is only sees nouns as an aspect. As such, in a sentence like “It was delivered quickly” the reviewer is mainly talking about the delivery, but because it is expressed as a verb, spaCy won’t detect it as an aspect. However, it can be said that most aspects the reviewer is talking about are articulated as a noun and therefore this drawback won’t affect the results too negatively.

| Example | Extracted Targets | Extracted Targets + Sentiment |
|---|---|---|
| The laptop is great | laptop | laptop great |
| The touchpad is simply perfect | touchpad | touchpad perfect |
| Screen and speakers are awful | screen speakers | screen speakers awful |
| I am satisfied with the delivery | delivery | delivery satisfied |

Figure 5: Example aspect extraction.

3 Training the Model:

This part is needed for the following sentiment analysis and is mostly used through Scikit-learn. This module is regarded as the state-of-the-art machine learning algorithm for supervised and unsupervised problems (Pedregosa et al., 2011). Using the machine learning module Scikit-learn, a Support Vector Machine (SVM) can be trained. De Kok et al. (2018) trained and used an SVM for aspect detection. This trained model creates a feature vector of values for every instance that will be classified and the model is taught using training data to interpret these values. In the case of this paper, the accuracy of the SVM was compared to a Naïve Bayes model, with the latter performing better, due to an SVM generally needing more data to train. This trained Naïve Bayes can take in each review and assign each sentence to one or more aspects that were extracted with spaCy. Therefore, spaCy lists all the aspects that are available and the Naïve Bayes classifies each review sentence into one or more of those extracted aspects. E.g. “Delivery was fast. Unfortunately, the product was broken” the model will now assign the first sentence to “delivery” and the second sentence to “product”. In the later stages, the model will look for the sentiment within each assigned sentence.

4 Sentiment Analysis:

For this part of analysis, first a few modules were loaded that are according to Marrese-Taylor et al. (2014), Ding et al. (2008), Rantanen et al. (2019) and Urologin (2018).

First, opinion lexicon by Hu & Liu (2004). These researchers defined a list of around 6.800 of positive and negative words designed especially for sentiment analysis and this lexicon is widely adopted in the NLP community. The researchers defined the lexicon by mining and summarizing customer reviews, then extracting the opinion sentences and predicting whether the opinion is positive or negative. Using this lexicon, the code can detect if a word that an aspect is associated with is either positive or negative. This lexicon was used in researches such as of Marrese-Taylor et al. (2014) or Ding et al. (2008) where it was needed for aspect based opinion mining. Another possible opinion lexicon could be SentiWordNet that automatically assigns a score to a term, however according to Na et al. (2009), this lexicon does not handle the opinion scoring problem and therefore, the lexicon of Hu & Liu was chosen for its simplicity.

```
text = "The product is great, however it is smelling bad"
replace_pronouns(text)

'The product is great, however the product is smelling bad'
```

Figure 6: Example replacing pronoun.

Second, Google’s pretrained word2vec model. This model was published by researchers of Google

(Mikolov et al., 2013) that trained the model on 1.6 billion words and it can recognize similarities of words. Thus, it is able to find words that are similar to the aspects and group them. This model is also heavily utilized in textual analysis with researchers such as Rantanen et al. (2019) using it to compute corporate reputation from social media comments. Another state of the art word embedding method is Global Vectors for Word Representation (GloVe) which was published by researchers of Stanford (Pennington et al., 2014). However, according to the study of Lin et al. (2015) where both wor2vec and GloVe were compared, word2vec performed better.

Third, neural coreference model is used to identify pronouns and replace them, as pronouns do not add any sentiment or weight. This pre trained neural network model can detect dependencies within a sentence and for example understand which terms refer to each other. According to Lee et al.(2017), this model outperforms all previously related work. Replacing pronouns is an important step according to Urologin (2018), as pronouns are just placeholders for proper nouns and this could affect the scoring of the sentiments. An example would be "The product is great, however it is smelling bad". The pronoun would be "it" which refers to "product", therefore the sentiment "bad" would be assigned to the term "it" and not "product" and using the neural coreference model, "it" will be replaced with "product". Figure 6 is an example of how a pronoun is replaced.

In the next steps the functions are defined that will make up the analysis. The functions consist of first checking for similarities of the words. The maximum similarity is 1, meaning it is the same word and it will be checked if the term is similar to the aspect. The threshold is set at 0.3, which garnered results where perceived similar words are detected where the penalty is not too high nor too low. E.g. "product" and "brand" have a similarity of 0.50 thus brand is similar to the aspect product and will be later assigned to that aspect. Now all the predefined aspects of Figure 1 will receive sentiment scores. First, it will be checked if the sentiment word like "great" is in the opinion lexicon and a sentiment score of +/- 1 will be given out accordingly. If there is an adjective modifier such as "incredibly", the sentiment will receive a greater weight of +/- 1.5. Negations such as "not good" will have the score flipped. Figure 7 gives an insight to the scoring.

Now the scores for all the aspects of Figure 1 will be accumulated and the scores of the synonyms will also be calculated. For example if the aspect "product" has been mentioned positively 10 times it will have 10 points, if the synonym "brand" has been mentioned positively 5 times the 5 points will go to the aspect "product", because according to word2vec the similarity is above the threshold of 0.3 and the aspect "product" will have overall 15 points.

```
#Test code for feature sentiment
sentence= "The delivery was smooth, but the product was bad"
feature_sentiment(sentence)
```

```
Counter({'delivery': 1, 'product': -1})
```

```
#Further test: Adjective intensifiers
sentence= "The delivery was incredibly good, but the product was super bad"
feature_sentiment(sentence)
```

```
Counter({'delivery': 1.5, 'product': -1.5})
```

```
#Further test: Negation words like "not"
sentence= "The delivery was smooth and the product was not bad"
feature_sentiment(sentence)
```

```
Counter({'delivery': 1, 'product': 1})
```

Figure 7: Example sentiment scoring.

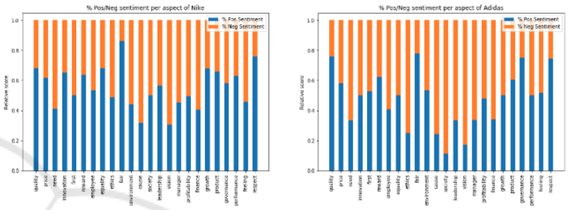

Figure 8: ABSA output for corporate reputation.

## 5 Visualization and Evaluation:

The last step is visualizing the results using the results garnered from previous step. Using tables, bar graphs or pie charts, the result of the sentiment analysis can be plotted to give an overview of the results. Matplotlib and Plotly were used of this step. Figures 8-10 are example output of the analysis applied to Adidas and Nike. Note that all aspects and scores directly relate to the relevant variables and dimensions in the corporate reputation model of Fombrun et al. (2015) that was shown in Figure 1.

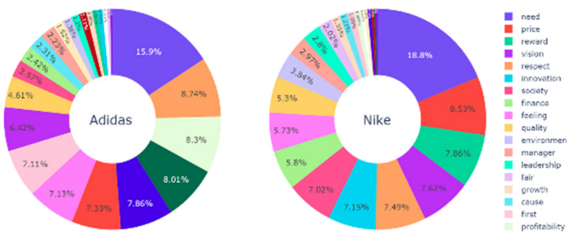


Figure 9: Aspects mentioned for corporate reputation.

The pos/neg ratio of aspects was calculated as follows in order to measure corporate reputation overall as well as within its dimensions and variables:

$$Pos\ ratio = (Sum\ pos\ points\ per\ aspect) / (Sum\ pos + neg\ points\ per\ aspect) \quad (1)$$

$$Neg\ ratio = \ (Sum\ \ neg\ points\ per\ aspect) /(Sum\ \ pos + \ neg\ points\ per\ aspect) \quad (2)$$

The overall relative positive sentiment score on Nike's corporate reputation was higher than that of Adidas on this dataset. We carefully checked on this for evaluation purposes, and it was in line with the average star rating of Trustpilot reviewers that was also available in our scraped dataset and that is publicly visible on the website.

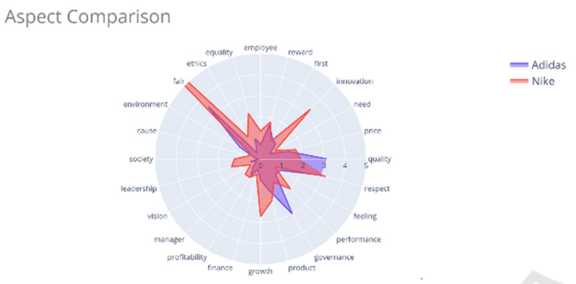


Figure 10: Aspect comparison for corporate reputation.

### 3.3 Validity

In order to validate our approach, we compared the overall scores obtained on both sides in the corporate reputation model (see dimensions 1 and dimensions 2 in Figure 1). On the left side in the corporate reputation model (dimensions 1 In Figure 1), we also compared, for each dimension, the average score on all attributes per dimension with the direct score on the dimension; e.g. the average score on "High quality", "Good value", "Stands behind" and "Meets customer needs" is compared with that on "Products". For Nike and Adidas together, the difference in score between dimensions 1 and dimensions 2 is 4%. The difference in score between averaged attribute scores and direct dimension scores is 7%. Despite that the scraped dataset is not extremely large, these low scores seem to imply the internal validity of our approach. Of course, such validity was already reported by Fombrun et al. (2015) based on their research with surveys. However, the important contribution that we aim to make in the corporate reputation literature is to be able to claim it for online review data on the public web.

## 4 CONCLUSION

In summary, with our approach, companies are enabled to assign to each aspect, that can be flexibly defined to corporate repution or to another relevant construct, a sentiment score derived from online reviews on the web.

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