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TRIPADVISOR REVIEWS ON MICHELIN-STARRED RESTAURANTS: A SENTIMENT ANALYSIS

João Miguel Miranda Mimoso

Dissertation presented as the partial requirement for obtaining a Master's degree in Information Management

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ABSTRACT

Nowadays, consumers are largely influenced by peer reviews about a product they intend to buy or a service they want to use. This behavior affects not only companies that sell consumer goods, but also restaurants, hotels, and other travel-related products. On platforms like Zomato or TripAdvisor, consumers can review restaurants they have previously visited by giving them a star rating, and by leaving a more comprehensive comment — a written review. This paper focuses on reviews given to Michelin-starred restaurants, and helps us understand if and how each customer's sentiment changes whenever a restaurant is awarded a Michelin star. Additionally, this paper analyzes the sentiment around the main restaurant dimensions (food, price, service, and ambiance), and identify which ones are influenced the most by the award.

KEYWORDS

restaurant reviews; TripAdvisor reviews; sentiment analysis; restaurant quality; Michelin-starred restaurants

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1. INTRODUCTION

Dining is one of the top five tourist activities in leisure trips (Pizam et al, 2004). When choosing a restaurant, there are many factors to take into consideration. One of those factors, which influences the consumer decision, is peer recommendations, such as online reviews (Libai et al, 2010; Van Doorn et al, 2010). With the increased use of the internet and social platforms (Hennig-Thurau et al, 2010), an individual opinion can now reach thousands of people. Consumers don't just rely on their friends' opinion; they place their trust in a much wider group of people that have already used a service and had something to say about it. Such behavior has increased the influence of online reviews on consumer decisions since they have become the new word-of-mouth, and customers find them trustworthy and reliable (Banerjee et al., 2017).

High review scores on platforms like Zomato or TripAdvisor are one of the most important success measures in business, so it's only natural that restaurants work hard to achieve them. When the time comes for consumers to decide where to go for a meal, restaurants need to have good opinions from previous customers to positively influence the former's decision in visiting their establishment. For this reason, restaurants need to increase their high-quality reviews, as well as decrease negative reviews. To do so, there is a need to understand what customers usually dislike when giving negative reviews, and what they find appealing when giving positive reviews.

Another source of trust when evaluating restaurants is the Michelin Guide. The guide book appeared in the beginning of the 20th century to encourage more drivers to take the road, and to help them plan their trips. In the beginning, it was just a "small guide filled with handy information for travelers, such as maps, information on how to change a tire, where to fill up on petrol, and a listing of places to eat or take shelter for the night." (guide.michelin.com). Back then, it was delivered at no cost; however, in 1920, a new Michelin Guide was launched. Years later, it started awarding restaurants with stars (from one to three); anonymous inspectors visited restaurants and attributed them stars based on some quality attributes. Today, the Guide also awards other prizes of excellence to restaurants that offer good quality, but not enough to deserve a Michelin star. The Michelin Guide created an elitist paradigm in the restaurant industry: on one side, the top-quality segment; on the other side, a massive group of restaurants ineligible for an award or even an evaluation (Pacheco, 2018).

Past works have revealed how much online reviews influence buyers' purchase intention (Hennig-Thurau et al, 2010; Libai et al., 2010; Van Doorn et al, 2010), and consequently how it affects sales (Feng Zhu et al, 2010). Several tools help us understand the trustworthiness of reviews, how they affect business (Banerjee et al, 2017), and what are the pros and cons of individual reviews. A number of other studies were conducted based on text mining, so as to understand customers' dining preferences (Huy Quan Vu et al, 2017), and even which factors of the reviews affected the rating (Qiwei Gan et al, 2017). These studies take a number of variables into account, such as the restaurant's geographic region or their price range, but they don't take into account variables such as the fact of a restaurant having a Michelin star. More recently, Pacheco (2018) analyzed the correlation between four dimensions (food, service, price, and ambiance) and the overall customer satisfaction. To do so, he analyzed the quantitative part of TripAdvisor reviews on Michelin-starred restaurants in Portugal and Spain.

However, there is a research gap in the literature. We know that food and service are the dimensions that contribute the most to the customers' overall satisfaction (Pacheco, 2018), but we don't know how the customers' perception of restaurant quality changes when a restaurant is awarded with, for instance, a Michelin star. In other words, what is the impact of an external event to the opinion of consumers. Hence, the aim of this study is to unveil how the perception of customer changes on this segment of restaurants. This can lead to generalizations, but every stakeholder can benefit from this knowledge and apply it to a specific case.

In this study we address three research questions: i) Does the award of a Michelin star affect customers' overall sentiment towards the restaurant? ii) What are the dimensions (food, service, price, and ambiance) that are affected the most and the least when a restaurant receives a Michelin star? iii) What are the dimensions that affect the overall sentiment the most? By answering these questions, we aim at understanding how the attribution of a Michelin star affects customers' perception of a restaurant, and which dimensions are influenced the most by this change in perception. Ultimately, we aim to understand the weight of Michelin stars when a customer is reviewing a restaurant.

The remainder of this paper is organized as follows: Section 2 summarizes the literature review of online reviews, Michelin-starred restaurants, text mining, and sentiment analysis; Sections 3 and 4, present the conceptual framework and research hypothesis; followed by the methodology used in the analysis; Section 5, discusses the results and main findings of our study and lastly, in Section 6 the main limitations identified in the elaboration of this study, and open lines of research for future research endeavors are summarized.

2. LITERATURE REVIEW

In this section we start by discussing how online reviews have evolved during the past few years, while summarizing the major findings derived from their analysis. Next, we follow with a discussion on Michelin-starred restaurants, the Michelin Guide, and how it works. Some emphasis was given to a 2018 article focusing on these restaurants. Last, there is the literature review about text mining and sentiment analysis, since these are a big part of our research analysis.

2.1. ONLINE REVIEWS

Electronic word of mouth, also known as eWOM, has spread in the last few years. Litvin et al. (2008) defined it as “all informal communications directed at consumers through Internet-based technology related to the usage or characteristics of particular goods and services, or their sellers”, based on Westbrook’s 1987 WOM definition.

One of the forms that eWOM can take is online reviews and these can “be defined as peer-generated product evaluations posted on the company or third-party websites” (Mudambi et al, 2010). Online reviews can be found in retail, restaurant, hotel and services websites, such as TripAdvisor, Zomato, or Yelp. Amazon.com initiated the rating system in the late 1990s and since then, it has become a widely used tool (Bilgihan, Seo & Choi, 2018). These can usually be composed of two components: a quantitative review (usually from 1 to 5 stars) and a qualitative review, i.e., a written comment.

Gretzel and Yoo (2008) found that travelers’ reviews increase confidence and reduce the risk of regretting a purchase. When it comes to restaurants, the behavior is similar. When the moment comes to decide which restaurant to choose, there are many factors that come to consumers’ minds; but one thing that highly influences their decision is peer recommendation like online reviews (Hennig-Thurau et al., 2010; Libai et al, 2010; Van Doorn et al, 2010).

In fact, consumers trust online reviews and there are studies that aim to understand what characteristics from the reviewers affect their trustworthiness the most and propose a model that can be used to predict reviewers trustworthiness (Banerjee et al, 2017). There were also conducted studies to understand how online reviews affect sales. Feng Zhu et al (2010), state that the previous researches are not conclusive when it comes to the effect of reviews on sales, and that it is expected that these reviews affect products that are exclusively sold online, rather than the ones sold offline. Even if we don’t find a direct correlation between both, we can understand that online reviews have an influence on sales based on their trustworthiness and the amount of positive or negative reviews.

In the past, researchers have defined food, service, ambiance and price as the fundamental aspects of a dining experience (Qiwei Gan et al, 2017). When it comes to sentiment analysis, Qiwei Gan et al (2017) also found , after proposing the fifth aspect, that food, service, and context are the top three dimensions affecting star ratings, followed by price and ambiance.

Due to the importance of online reviews, companies found that they can have major gains from them by producing fake reviews in order to promote or damage the reputation of a product (Mukherjee et al, 2019). These reviews are written by users with little or no experience with the product (Zhang et al, 2016). Dozens of companies, including Samsung, were accused of producing fake reviews. Some companies even advertise on websites such as Craigslist, looking for writers to write fake reviews for them (Zhang et al, 2016). This affects various industries, such as telecommunications, streaming services, online marketplaces, and the restaurant industry. Ott et al (2012), discovered that deceptive opinion spam is a problem that is growing in all of the studied platforms: Yelp, TripAdvisor, Priceline, Orbitz, Hotels.com, and Expedia.com. One infamous case about fake reviews on TripAdvisor is the one about The Shed at Dulwich: a non-existing restaurant that started ranking in 18149th place and became, a few months later, the top-rated restaurant in London. In the Michelin-starred segment, this is not a problem. These restaurants have a signature cuisine, worldwide credibility, and were awarded a star by the Michelin Guide, providing them with great credibility.

2.2. Michelin-starred Restaurants

The Michelin Guide is a book that was launched, as we know it, in 1920 to encourage drivers to take the road. In 1926, the guide began to award a star to the best restaurants and, some years later, the system of 1, 2, and 3 stars was introduced (guide.michelin.com). Nowadays, this guide is a reference in the cuisine world.

Michelin inspectors walk into restaurants anonymously and evaluate them according to the quality of their products, mastery of flavor and cooking techniques, the personality of the chef in his cuisine, value for money, and consistency between visits.

In the past, very few studies were conducted focusing on Michelin-starred restaurants, Pacheco (2018) used customer reviews of Michelin-starred restaurants in Portugal and Spain to analyzethem in terms of overall satisfaction in four different dimensions: food, service, atmosphere, and value. This study identified food and service as the dimensions contributing the most to the overall satisfaction in three different segments: restaurants with one, two, and three Michelin stars. This study has some limitations that leave room for future analysis, such as the analysis being performed only in Portugal and Spain, and being only performed on the quantitative part of the reviews.

Snyder & Cotter (1998) studied the correlation of getting a Michelin star and how this would affect the restaurants' price strategy. They discovered, among other things, that most restaurants that received a Michelin star increased their prices before getting the award. They also concluded that after receiving a Michelin promotion, restaurants tried to catch up with the other restaurants already in the higher category in terms of pricing strategy.

2.3. Text Mining and Sentiment Analysis

Text Mining can be defined as a process of discovering hidden useful patterns from unstructured sets of data, in this case, composed by text. Hence, another definition of Text Mining is Knowledge Discovery in Text. It offers various benefits to organizations such as analyzing brand reputation online and understanding customers' opinions (Moro et al., 2017; Oliveira et al., 2019)..

Text Mining is divided into three steps: tokenization, stop word removal, and stemming (Sumathy et al, 2013). Tokenization is the process of normalizing text by removing full stops, commas, and empty spaces. Stop word removal is, as the name indicates, the removal of all words (and tags like HTML tags) that don't add any value to the analysis, as well as stop words themselves such as "if". Lastly, stemming is the process of identifying the root of words and have them normalized.

Sentiment analysis (or opinion mining) can be described as the field of study that analyses people's opinions, sentiments, and emotions towards a product, service, company, or any other subject (Liu, 2012). Mostafa (2013) adds that it is a natural language processing application that uses computing power and text mining to identify sentiments, usually positive, negative, or neutral.

Analyzing this data on user's restaurant reviews from online platforms can represent huge benefits to companies and can make them turn negative reviewers into brand advocates. For this reason, there are studies, like Nave, Rita and Guerreiro (2018), that propose a Decision Support System (DSS). The system can help managers develop insights and define strategies that are more in line with the customers' expectations.

In the field of sentiment analysis, there are also studies that analyzed consumer reviews using topic modeling with the help of algorithms tools in the hospitality industry (Calheiros et al, 2017; Moro et al., 2019). These studies are especially important when giving insights to stakeholders in a specific industry, such as the hospitality, restaurant, or medical industries, for instance. Using topic modeling can give better insights of customers' reviews and help stakeholders take better and more informative actions.

3. CONCEPTUAL FRAMEWORK AND RESEARCH HYPOTHESES

3.1. CONCEPTUAL FRAMEWORK

Figure 1 shows the relationship between the multiple variables that compose our analysis. Sentiment around price, food, service, and ambiance are independent variables. These were chosen based on the fact that "researchers have generally agreed that food, service, ambiance, and price are the four fundamental aspects to make up consumers' dining experiences" (Qiwei Gan et al, 2017). Therefore, by analyzing the sentiment around these four dimensions, we can understand which ones are affecting the overall sentiment the most. On the other hand, the number of Michelin stars and the award of the star itself are control variables. Since the analysis that we are performing is intended to answer how the overall sentiment of customers changes when a restaurant receives a Michelin star, the award of a Michelin star is an important variable. This let us pinpoint the date of the award and understand how the sentiment was before and after this date. Another variable that adds value to the analysis is how many stars a restaurant has. For instance, the impact of receiving the first Michelin star might be different compared to when a restaurant adds another one to its portfolio. The star rating and local language variables allow us to get a deeper understanding of how the language of the review and the given star rating are correlated to the overall sentiment. Finally, we have the overall sentiment, which is a variable that depends on the remaining ones. This is the main variable to study in our analysis.

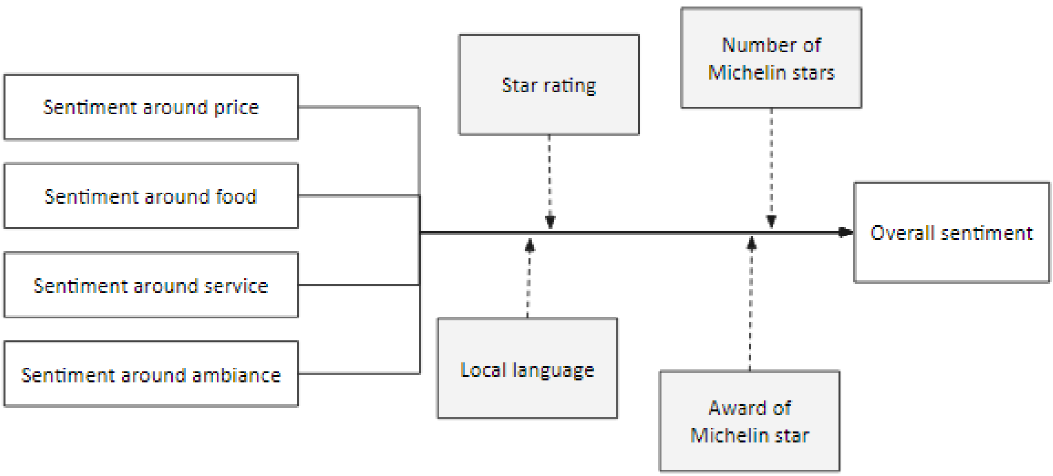

Figure 1 - Conceptual Model – effect of the dependent and control (grey) variables on the overall sentiment

3.2. RESEARCH HYPOTHESES

According to Yoon et al (2019), consumers are influenced by others' reviews, meaning that when consumers review a restaurant, they pay attention to the experiences and opinions of others first. This suggests that there is a social influence in the process of writing online reviews. Because of this, there is reason to believe that the award of a Michelin star will positively influence consumers satisfaction and increase the sentiment towards the restaurant. Thus:

H1: The overall sentiment will increase when a customer evaluates a restaurant.

Snyder and Cotter (1998) studied the relationship between a restaurant receiving (or losing) a Michelin star and its price strategy. The findings suggest that when the Michelin rating changes for a restaurant, that change is reflected in the price. Therefore, with the probable increase in the restaurants' prices, customer satisfaction around this dimension will decrease. Hence:

H2: The sentiment around price will decrease due to the increase in prices in Michelin-starred restaurants when they receive a star.

From the four dimensions that we are analyzing, food and service are more correlated to customers' overall satisfaction in the segment of Michelin-starred restaurants (according to Pacheco,2018). For this reason, when a star is awarded a Michelin star, it is expected that these two dimensions are affected the most. Consequently:

H3: Food and service will be the most affected dimensions due to their impact to the overall customer satisfaction in this segment of restaurants.

Also, according to Pacheco (2018), ambiance (or atmosphere) is the dimension that is less correlated to the overall satisfaction of customers of Michelin-starred restaurants. For this reason, when a star is awarded, it is expected that ambiance is the dimension that is less affected. Thus:

H4: Ambiance will be the dimension with fewer changes due to its weaker connection to customer satisfaction.

Finally, when a restaurant receives the first Michelin star, the chances of having a difference in the sentiment are bigger because it is joining a new segment - the Michelin-starred restaurants segment. When a restaurant increases from the first to the second or second to third star, the expectations are already set because the restaurant already has a Michelin star. Hence:

H5: The overall sentiment will suffer a bigger change when a restaurant receives the first star.

4. DATA AND METHODOLOGY

The approach to tackle the subject of this paper is based on *Knowledge Discovery in Database* (KDD) (Tan, Steinbach, and Kumar 2006), turning raw data, i.e. individual reviews, into relevant information that delivers value to the reader. This data is not stored in traditional databases, but on TripAdvisor (www.tripadvisor.com), an online platform that allows users to review restaurants and other hospitality services. We also got a list of Michelin-starred restaurants (www.viamichelin.com) and their number of Michelin stars, type of cuisine, and location.

For this analysis, a list of 35 restaurants that were awarded a star in the 2018 Michelin Guide was created. The restaurants that compose this list are located in Europe and have 1, 2, or 3 Michelin stars, by the time of the 2018 Michelin Guide release. Moreover, a list of 2375 reviews related to these restaurants was retrieved from TripAdvisor. In addition, a list of 52 restaurants that were not awarded a star but are similar in price, rating, location, and cuisine, was added to be used as a control group. Finally, 6611 reviews about these restaurants were also retrieved.

To be turned into information, the collected raw data needed to be filtered, transformed, mined and, finally, interpreted.

Information from TripAdvisor was extracted using a web crawler developed using BeautifulSoup, a Python library for parsing HTML. From each restaurant it was extracted its name, price range, text review, star review and date of the visit. Information like restaurant name and price range are provided by the restaurant representative (manager or owner) and they can be used to categorize restaurants. Reviews are provided by users and these are sets of unstructured data that need to be processed after the crawling. Information like the date of the visit is also provided by users and can be used to segment them. For this step we used a python script (appendix 1) that crawled TripAdvisor's website, getting the name of the restaurant, date of the visit, star review, and a written review. After getting the reviews, those were stored in CSV (comma-separated values) files and, later, uploaded to a sentiment analysis software.

The second step that needed to be performed was Data Processing. Here we crossed both sources of data, organized and prepared the data to perform the sentiment analysis. The properties of our data set are described in the following table 1.

Category	**Property**	**Description**
Restaurant	Restaurant name	The name of the restaurant.
	Michelin stars	The number of Michelin stars the restaurants has at the date of this analysis, after the award.
	Restaurant location	The location of the restaurant.

	Price range	The restaurant price range extracted from the Michelin website.
Review	Star rating	The quantitative part of the review. It is a rating that ranges between 1 and 5.
	Written Review	The qualitative part of the review. This is a type of unstructured data and it is on this property that we will conduct a sentiment analysis. Here, we only considered reviews written in English.
	Date of visit	The date of the visit of the reviewer. We only considered reviews given 6 months before and after the award. This allows us to narrow the time frame, eliminate other factors that could lead to eventual changes and increase the likelihood of the changes being a result of the award.
	After award	This is a binary property to separate the reviews given before and after the awfard. 0 means the visit happened before the award and 1 after the award.
	Local language	This is a binary property that separates reviews written in the local language of the country (1), i.e English in the United Kingdom, from reviews written in English where it is not the local language (0).

Table 1 – Dataset properties description

To process the data, the reviews had to be uploaded into a tokenization algorithm, in which the reviews were broken into words, phrases, symbols and other elements that we call tokens. In this process the words were normalized, all letters were turned into lower case and all symbols and numbers were removed. Also, words like “loved” and “loving” were turned into “love” (verb). Then each word was tagged with a type (noun, verb or adjective) and categorized according to Lexalytics concept topics (Lexalytics, 2015) and user-defined ones (figure 2). After this, these words were matched with a large set of words and sentiments will be applied to those (positive, negative or neutral) based on sentences inside a review.

For this process, we used Semantria, which uses lexicon-based linguistic information and rules to detect sentiments in short sentences. It also uses lexical chains to create topic-specific summaries in text. Semantria uses synonym expansion and other techniques to construct chains of topics in pieces of text (lexalytics.com). Semantria also analyzes entire documents (reviews) and gives them a sentiment score from -3 to 3, and components (queries, entities or topics) from -10 to 10, where the negative end represents an extremely negative sentiment and the positive end an extremely positive sentiment. This range varies depending on the configuration. These documents and components also receive a tag (negative, neutral and positive) depending on the sentiment score. A document sentiment is considered negative when it is smaller than -0.05 and positive when it is bigger than 0.22 (the remaining are neutral). A component sentiment is negative when it is lower than -0.45 and positive when it is greater than 0.5. The software also uses modifiers that affect the sentiment, such as intensifiers (very, a lot, super, etc) and negators (not, never, etc). Moreover, Semantria has industry packs which contain queries, topics, and categories that are related to the restaurant industry. Some words might be seen as negative in a certain context, but it can also be positively perceived in the restaurant world. One example could be the word "explosion", which has a negative connotation in general; however, in the restaurant world, the phrase "explosion of flavors" is commonly used. For this reason, industry packs are essential for the analysis.

After the pre-processing, the data was analyzed. During this step we not only analyzed the reviews in general but also took into consideration the most relevant dimensions: price, food quality, waiting time, waiters service, the physical environment and other dimensions that came up during the analysis. Afterwards, we grouped them in the four dimensions that we identified before: price, food, service, and ambiance. These steps let us know the sentiment around the four main dimensions. To do so, we created a taxonomy in Semantria with the help of an industry pack, that allowed us to group queries and dimensions in a hierarchical way that is visible in the figure 2. This means that dimensions and queries were grouped under a parent dimension and the sentiment around them represened the sentiment around the main one, i.e., our four main dimensions.

Figure 2 - Semantria taxonomy queries grouped into our four dimensions

5. RESULTS AND DISCUSSION

5.1. RESTAURANTS

As previously mentioned, the data set is based on European restaurants that received a Michelin star in the 2018 Michelin Guide. The criteria to choose these restaurants was that they should have more than 20 reviews in the previous or following 6 months after the award. The difference between the number of reviews given before and after the award should be small, so we excluded the cases where one period represented 70% or more of the total amount of reviews for that restaurant.

In 2018, 58 restaurants in Europe received the first star, 9 received the second star, and 4 got their third star. In our data set, we have restaurants from the three segments, distributed as represented in the following table 2.

Group	Number of stars	# Restaurants	% of group total
Control Group	0	52	100%
Michelin Group	1	26	74.29%
	2	6	17.14%
	3	3	8.57%

Table 2 - Number of restaurants in our sample according to the number of Michelin stars they owned after the award

This means that our data set incorporates 45% of the restaurants that received the first star, 67% of those who received the second star, and 75% of the ones that received the third star, making a total of 35 restaurants. It is noticeable that the number of restaurants that received their first star is much higher, which may influence the results.

Regarding the location, the same behavior can be observed in some level. Since we decided to only include reviews written in English, the country with more restaurants matching the criteria is the United Kingdom, while the country that received most of the stars in 2018 was France, with 16 restaurants, and the United Kingdom and Spain coming in second place with 8 restaurants each. The following table 3 shows the geographic overview of this data set.

Country	Michelin Group				Control Group			
	# Restaurants	% of total	# Reviews	% of total	# Restaurants	% of total	# Reviews	% of total
United Kingdom	8	22.86%	967	40.72%	12	23.08%	2649	40.07%
Spain	6	17.14%	343	14.44%	8	15.38%	490	7.41%
Italy	6	17.14%	237	9.98%	7	13.46%	602	9.11%
Austria	4	11.43%	184	7.75%	8	15.38%	538	8.14%
Germany	3	8.57%	201	8.46%	4	7.69%	340	5.14%
France	2	5.71%	65	2.74%	4	7.69%	647	9.79%
Netherlands	2	5.71%	136	5.73%	2	3.85%	296	4.48%
Sweden	1	2.86%	21	0.88%	1	1.92%	59	0.89%
Denmark	1	2.86%	23	0.97%	2	3.85%	120	1.82%
Hungary	1	2.86%	175	7.37%	2	3.85%	568	8.59%
Finland	1	2.86%	23	0.97%	2	3.85%	302	4.57%

Table 3 - Geographic distribution of the restaurants and reviews

5.2. Reviews

From the 35 Michelin restaurants, 2375 English reviews were extracted from TripAdvisor. These reviews spanned a time period of one year, where 6 months are prior to the restaurant obtaining the Michelin star and 6 months after the that event. In doing so we attempted to control other factors that might explain variations in the sentiment other than the obtention of the award. On the other hand, 6 months allowed us to have a considerable amount of reviews. The awards were given at different dates depending on the country, Table 4 summarizes the dates for each country.

Country	Date of award
United Kingdom	17 October, 2017
Spain	27 November, 2017
Italy	16 November, 2017
Austria	26 March, 2018
Germany	15 November, 2017
France	5 February, 2018
Netherlands	11 December, 2017
Sweden	19 February, 2018
Denmark	19 February, 2018
Hungary	26 March, 2018
Finland	19 February, 2018

Table 4 - Date of Michelin star award per country

From the total amount of reviews in the Michelin Group, 77.5% were given to restaurants that received their first star in 2018, 18.31% to restaurants that received their second star, and 4.19% to restaurants that received their third star, as can be observed in Table 5.

Group	# of stars	Time of review	# Reviews	% of subtotal	Average Sentiment	Standard Deviation	% group of total
Control Group	0	After award	3083	47.03%	0.65	0.43	100%
		Before award	3472	52.97%	0.66	0.42	
		Total	6555	-	0.65	0.42	
Michelin Group	1	After award	845	47.08%	0.51	0.33	77.50%
		Before award	950	52.92%	0.54	0.36	
		Total	1795	-	0.52	0.34	
	2	After award	222	52.36%	0.53	0.31	18.31%
		Before award	202	47.64%	0.57	0.34	
		Total	424	-	0.55	0.32	
	3	After award	45	46.39%	0.42	0.34	4.19%
		Before award	52	53.61%	0.42	0.33	
		Total	97	-	0.42	0.34	
	Group Total	After award	1112	48.01%	0.51	0.32	100%
		Before award	1204	51.99%	0.54	0.36	
		Total	97	-	0.52	0.34	

Table 5 – Detailed review information per group before and after the award

When looking at the overall sentiment in both groups, we can see that it decreased from one period to another. In the control group, the decrease is approximately 2%, and in the 1- and 2-star segments, the decrease is about 5%, see Figure 3. In the 3-star segment, the decrease is less than 1%, but this segment represents only 4.19% of the group's reviews. The average decrease in the Michelin Group is 4.8%.

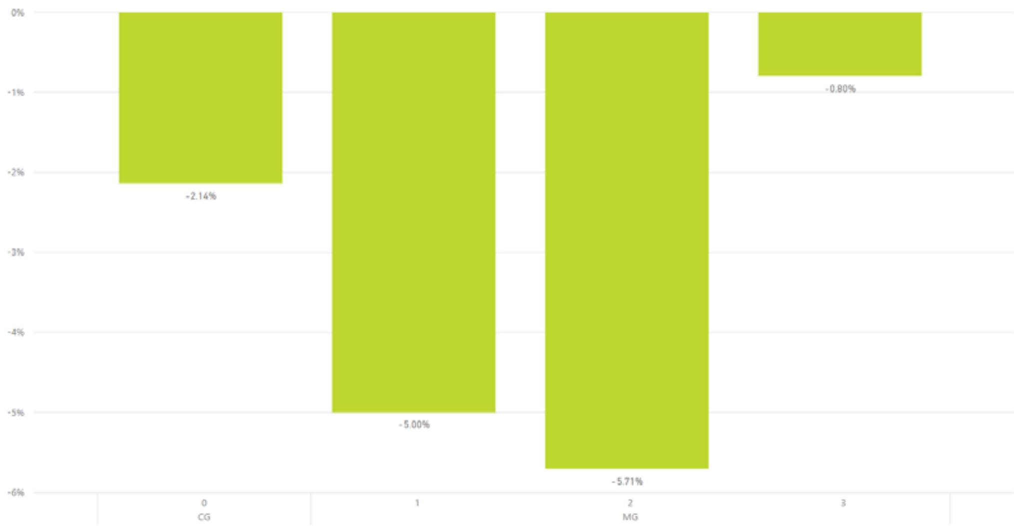

Figure 3 - Change in average sentiment from before to after the award in the Control Group (CG) and Michelin Group (MG)

A sentiment tag is attributed to each review (positive, negative, or neutral). Figure 4 shows that the percentage of positive reviews decreased after the date the Michelin star was awarded, while the number of neutral and negative reviews increased. These results can help explaining results in Figure 3 - an increase of the percentage of neutral and negative reviews and the reduction of the percentage of positive reviews may explain the decrease in the overall sentiment after the award.

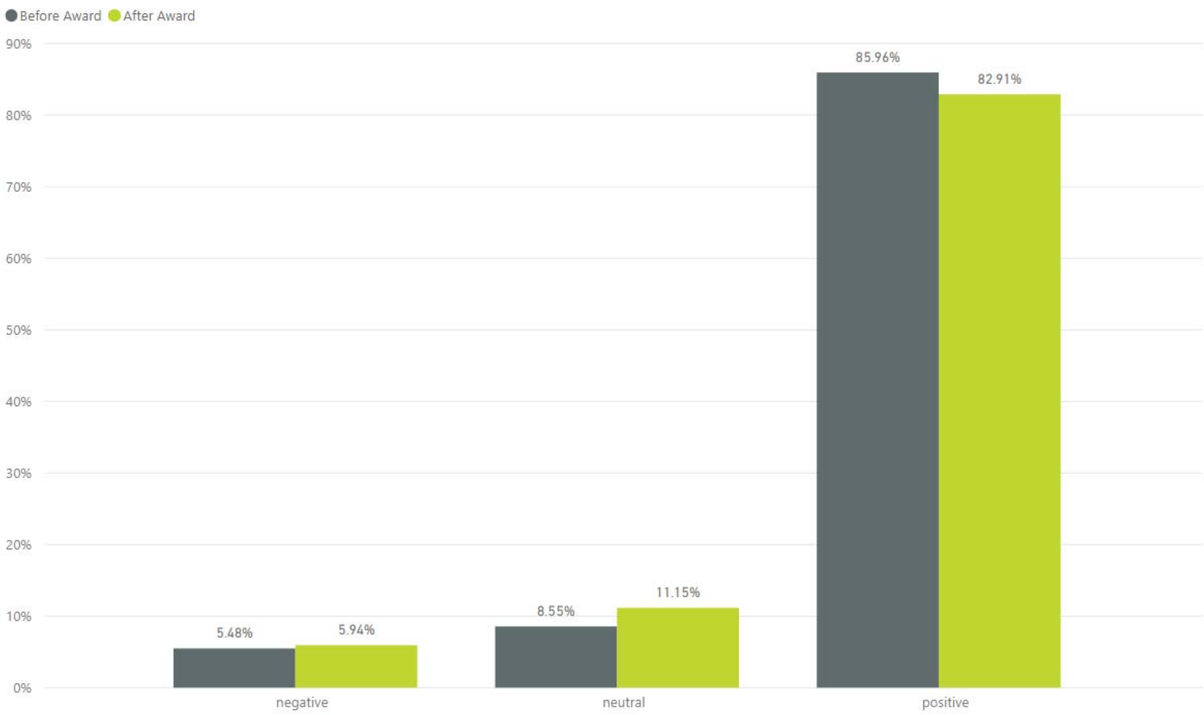

Figure 4- Reviews per sentiment before and after the award (Michelin Group)

As previously mentioned, besides the main object of the analysis - the written review - the star rating of each review was also extracted from TripAdvisor and, as expected, most of the reviews (87.83%) rated the restaurant with 4 or 5 stars (Table 6), where 71.5% rated the restaurants with 5 stars, resulting in an average of 4.5 out of 5. Moreover, when analyzing the reviews after and before the award, the average rating is the same, i.e. 4.5, leaving us with no conclusions about the change in customers' sentiment when a restaurant is awarded a Michelin star.

Star Rating	# Reviews	% of total	Average Sentiment	Standard Deviation	Average rating
1	51	2.20%	-0.04	0.33	
2	75	3.24%	-0.10	0.35	
3	156	6.74%	0.17	0.31	4.5
4	377	16.28%	0.43	0.28	
5	1657	71.55%	0.63	0.27	

Table 6 - Reviews' star rating

The average sentiment (represented with a dot in Figure 5) increases as the star rating increases, except in 1- and 2-star ratings. It is also possible to observe that only the sentiment of those who gave 2 stars is negative. The sentiment of those who rated 1 star is neutral, but very close to negative. The sentiment of those who rated 3 stars is neutral and the remaining (4 and 5 stars) are positive, as expected.

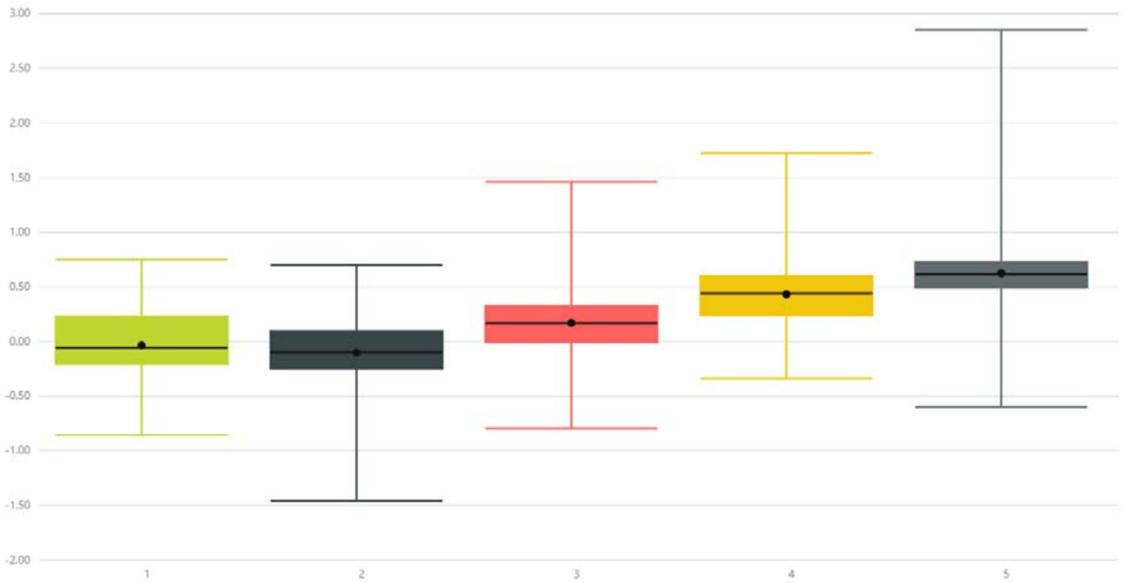

Figure 5 - Review sentiments per star rating with minimum and maximum value (whisker), average as dot, median as line, and the interquartile range as interval

In what regards the language of the review and the country of the restaurant (Table 7), we can identify foreign and domestic reviews; domestic being the ones written in English in an English-speaking country. There is a chance that these two types of customers have different opinions about the restaurants, but that behavior is not present in our sample.

Language	Time of review	# Reviews	% of subtotal	Average Sentiment	Standard Deviation	% of total
Foreign	**After award**	662	48.22%	0.53	0.34	59.28%
	Before award	711	51.78%	0.56	0.38	
	Total	1373		0.54	0.36	
Local	**After award**	450	47.72%	0.49	0.29	40.72%
	Before award	493	52.28%	0.51	0.32	
	Total	943		0.50	0.30	

Table 7 - Detailed review information per language – local and foreign

From the 2375 restaurant reviews (Michelin group), 13618 sentiments about service, food, ambiance, and price were extracted. From these sentiments, 40.48% mentioned the service, 41.38% mentioned the food, 11.37% mentioned the ambiance, and 6.76% mentioned the price. This tells us that the first two are more present in customer reviews and can confirm that these two are the dimensions that are most present in consumer minds when reviewing a restaurant. Both of these dimensions contribute the most to customers' overall satisfaction, as analyzed by Pacheco (2018).

When analyzing the sentiments for each dimension before and after the award (Table 8), we can notice that the average sentiment decreases in each one except for price, where it increases from 0.18 to 0.30, which are neutral values. As stated before, Snyder and Cotter (1998) studied that restaurants tend to increase prices before getting the award. This can lead to customers' dissatisfaction before the award and to acceptance after the award, due to its status.

Dimension	Sentiment	# Sentiments	% of subtotal	Average Sentiment	Standard Deviation	% of total
Service	**After Award**	2647	48.01%	0.99	1.15	40.48%
	Before Award	2866	51.99%	1.14	1.22	
	Total	5513	-	1.07	1.19	
Price	**After Award**	420	45.60%	0.30	0.92	6.76%
	Before Award	501	54.40%	0.18	1.09	
	Total	921	-	0.23	1.02	
Food	**After Award**	2798	49.65%	0.78	1.00	41.38%
	Before Award	2837	50.35%	0.86	1.01	
	Total	5635	-	0.82	1.01	
Ambiance	**After Award**	762	49.19%	0.57	0.86	11.37%
	Before Award	787	50.81%	0.60	0.85	
	Total	1549	-	0.59	0.86	
Total	**After Award**	6643	48.63%	0.81	1.06	100%
	Before Award	7016	51.37%	0.89	1.12	
	Total	13659	-	0.85	0.86	

Table 8 - Detailed sentiment information per dimension (Michelin group)

In figure 6, it is possible to observe the change in the sentiment around each dimension. While the change in the control group is stable, varying between -3.17% and -6.40%, the change in the Michelin group is not as stable. The sentiment around price increases by a big amount in restaurants that won their first or third star (~70%) and increased by ~29% in restaurants that won their second star. This can be explained again by the increase in prices before the award (Snyder and Cotter, 1998) and the possible dissatisfaction caused, which can lead to customers finding the price fair after the award is given, due to the higher status.

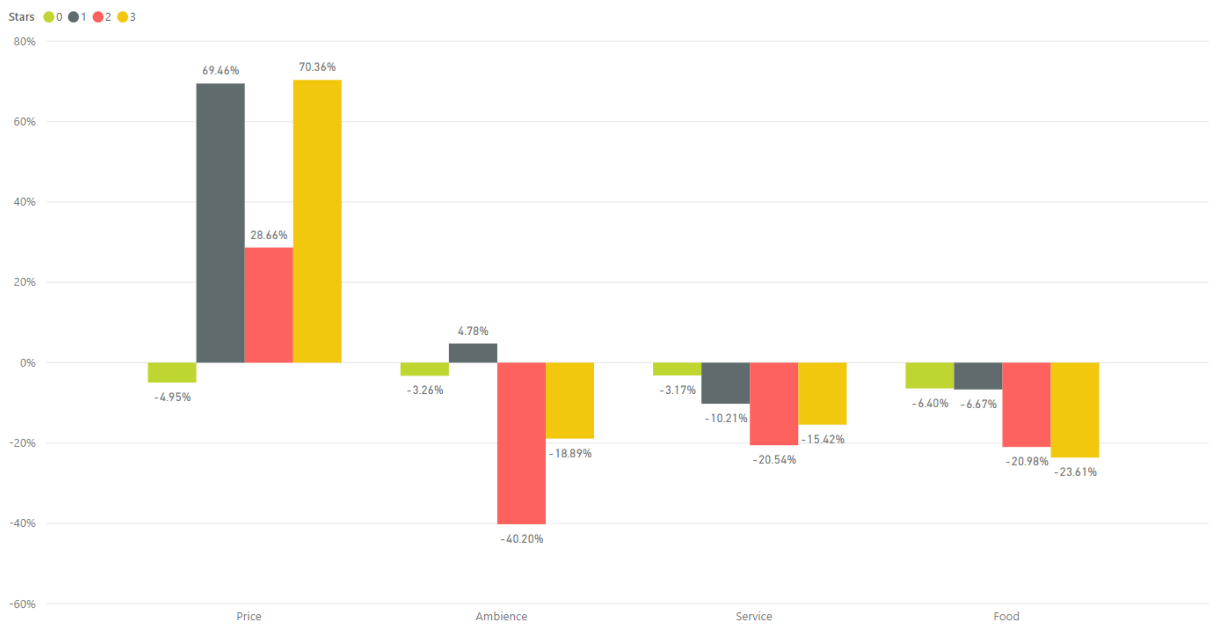

Figure 6 - Change per dimension and restaurant stars before and after the award (numbers define the stars after the award)

The overall results per group can be found in figure 7. The findings are similar to the ones visible in figure 6, but in this case it's clear that the increase in sentiment around price is much higher in the Michelin group, and the decrease around the other dimensions is also higher in the Michelin group.

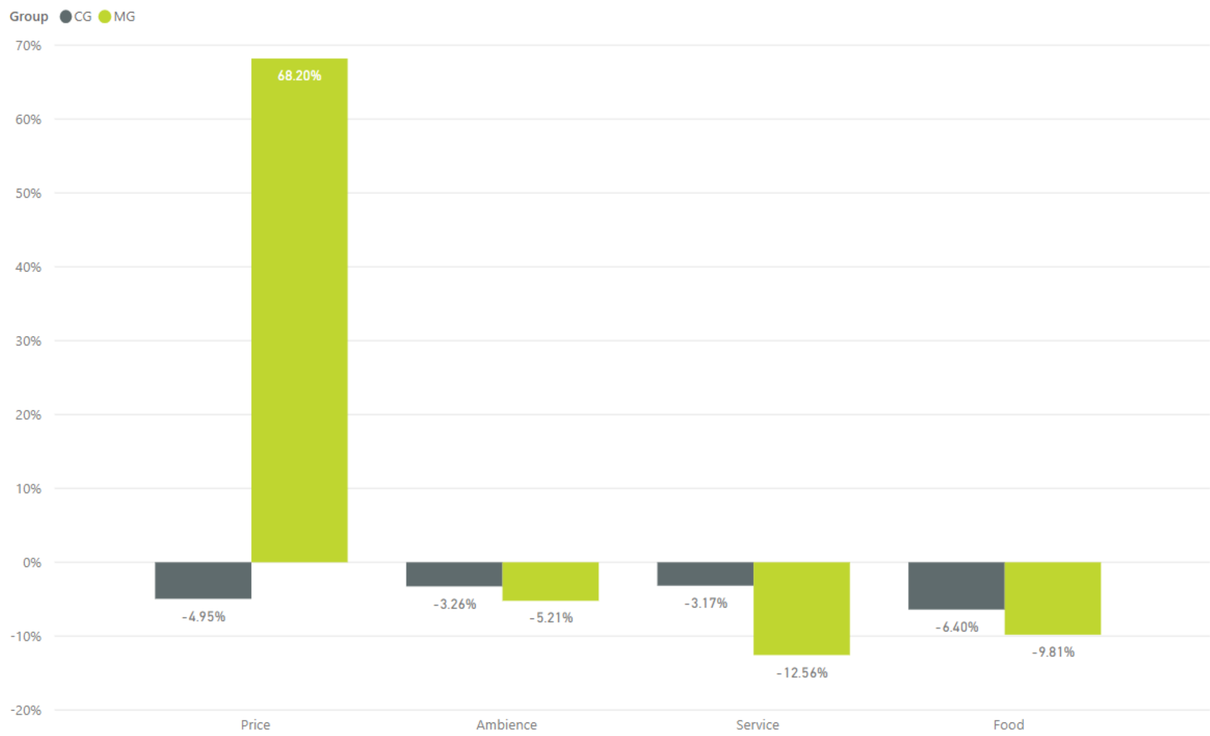

Figure 7 - Change per dimension and restaurant group – Control Group in grey and Michelin Group in green

To understand the correlation between the sentiment around the four dimensions and the overall sentiment before and after the award, two linear regressions were conducted (Table 9). Each regression aims to demonstrate the impact of the sentiment around each dimension, on the overall sentiment.

Constant: Overall Sentiment		
	Control Group	**Michelin Group**
Price Sentiment	0.092 (***)	0.12 (***)
Ambience Sentiment	0.043 (***)	0.056 (***)
Food Sentiment	0.086 (***)	0.046 (***)
Service Sentiment	0.094 (*)	0.103 (***)
Constant	0.229 (***)	0.232 (***)
R^2	0.585	0.508
N	6555	2316
Notes:	* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$	

Table 9 - Regression analysis - effect of dimensions on the overall sentiment

In both models, it is possible to observe that all our independent variables are statistically significant with a confidence interval of 95%. While in the Control group the sentiment around service is the one affecting the overall sentiment the most (closely followed by the sentiment around price and food), in the Michelin group, the sentiment around price is the one affecting the overall sentiment the most, where the increase of 1 unit in the Price Sentiment means an increase of 0.12 in the overall sentiment. After price, we have the sentiment around service and, last, the sentiment around ambience and food.

When compared to the Control group, the Food Sentiment in the Michelin group doesn't affect the overall sentiment as much as the other independent variables, while Price Sentiment and Service Sentiment have similar impacts in both groups. Nevertheless, the impact of ambience is small in both models.

5.3. DISCUSSION

We can observe in Figure 3 that the overall sentiment has decreased after the Michelin star award and, even though it decreases in both groups, the decrease in the Michelin Group is 2.65% higher, more than double of the decrease in the Control Group, which rejects our hypothesis 1. This can be a result of the decrease of positive reviews and an increase in neutral reviews (figure 4). A decrease can also be observed when analyzing the sentiment around our four dimensions. On average, in the Michelin Group, the sentiment around the dimensions decreased from 0.89 to 0.81, which represents a change of 8.9%. When analyzing each one of the dimensions, we can see a decrease of 12.56% in service, 9.81% in food, and 5.21% in ambiance, which validates our hypothesis 4. On the other hand, we can observe an increase in sentiment around price of 68.20%, which rejects our hypothesis 2.

When analyzing the values observed in the Control Group, we can see a decrease in sentiment around all dimensions between -3.17% and -6.40%. We can observe a big contrast in the sentiment around price, where the change in the Michelin Group is 68.2% and in the Control Group is -4.95%. Regarding the other dimensions – food, ambiance and service -, the behavior is similar, but the decrease is always higher in the Michelin Group.

The overall decrease in sentiment around dimensions – service, price, ambiance and food - can explain the decrease in customers' overall sentiment. Even with the big increase of sentiment around price, it only represents 6.76% of the total sentiments, while food and service represent over 80%, having more impact on the overall dimensions' sentiment. Our hypothesis 3 is also rejected by the fact that the sentiment around price represents the biggest change. Nevertheless, service and food are the dimensions that customers review the most (40.48% and 41.38% respectively), which means they are the most present dimensions in customers' minds.

When segmenting the restaurants by number of Michelin stars, we can see that there's a reduction in the overall sentiment in restaurants that won their first or second star, while in restaurants that won their third star, the sentiment didn't change. The segment that has a bigger change in sentiment is the one with restaurants that won their second star, and despite the change being so similar to the restaurants that won their first star, this rejects our hypothesis 5 (table 5).

In table 5 and figure 5, the reviews were segmented by their star rating and the obtained results were expected. When the star rating increases, so does the sentiment, except when the star rating increases from 1 star to 2 stars, although these two segments represent less than 6% of the reviews. This behavior was expected since the star rating is a numeric representation of customers' satisfaction.

6. CONCLUSION, LIMITATIONS AND FUTURE RESEARCH

This paper aimed to understand the effect of a Michelin star award in customers' overall satisfaction, as well as how price, food, ambiance, and service dimensions react to this event and how correlated they are to the overall satisfaction.

It was concluded that overall satisfaction decreases with the award of a Michelin star (-4.7%). This can be the result of customers' higher expectations due to the Michelin Guide distinction. In regard to the dimensions, price was the only one having an increase in sentiment, while the others had a decrease in sentiment. There was an increase in the sentiment around price of 68.2%, making it the most affected dimension. On the other hand, the sentiment around service decreased by about 5%, making it the least affected dimension. It was also concluded that price is the dimension that affects the overall sentiment the most, followed by service, food, and ambiance.

Despite these results, it doesn't mean that restaurants shouldn't work to get a Michelin star. Even though the sentiment doesn't increase after the award, the latter may increase the price per meal, the restaurant's exposure, and its reputation. Moreover, the award of the star may lead to a more demanding customer segment, which can justify this decrease in sentiment. Finally, while price isn't the most reviewed dimension, restaurateurs should keep in mind that it represents the biggest impact in customers' overall sentiment.

Since this study was based on a sample of reviews on European restaurants, so there is room to understand how the award and the identified dimensions affect the overall sentiment in different geographical areas, such as the United States of America, where there is a big concentration of Michelin-starred restaurants.

Furthermore, to have a relevant sample in size, we considered every review that was written 6 months before the award and 6 months after the award. This time range might include reviews that were affected by external factors and might influence our results, even with the use of a Control Group to minimize external influences. In addition, only reviews written in English were considered in this study, which can also influence the results in countries where English is not the mother tongue. Therefore, an analysis can be conducted in each country's local language.

Finally, the reason why the sentiment decreases with the award of the Michelin star was not identified. It might be related to the change of the target segment or even due to customers' higher expectations. A future analysis could be conducted to understand the reason behind this behavior.

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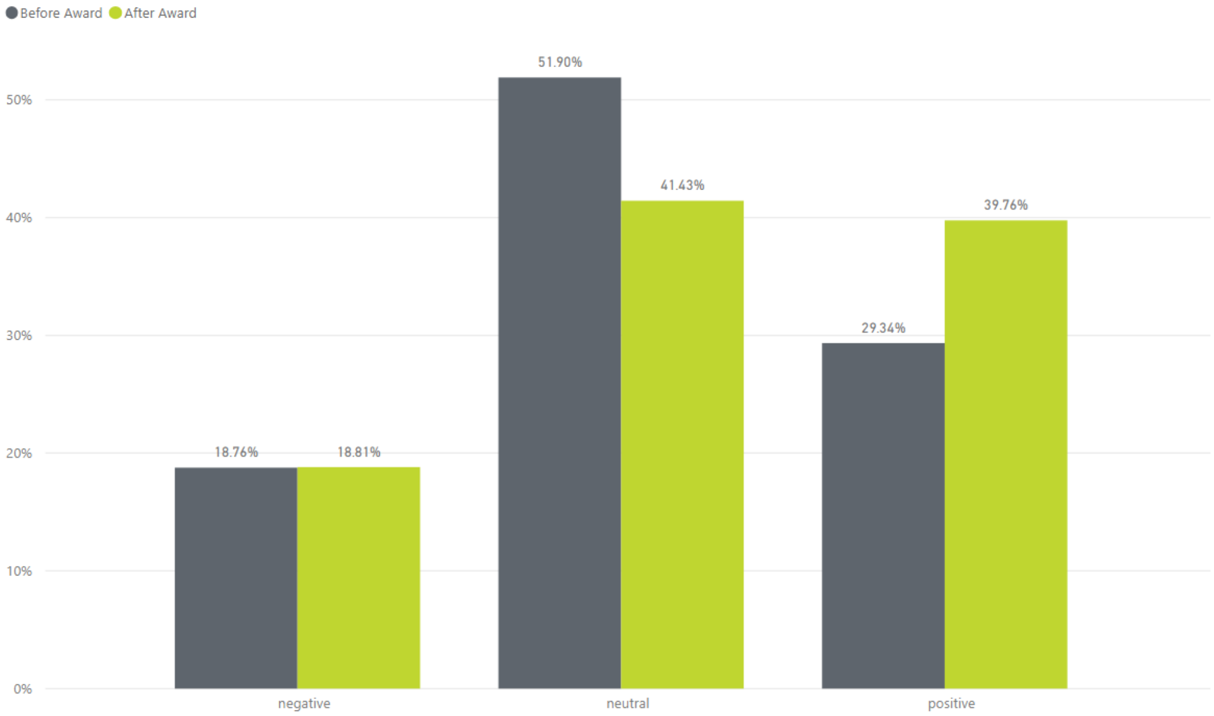
APPENDIX

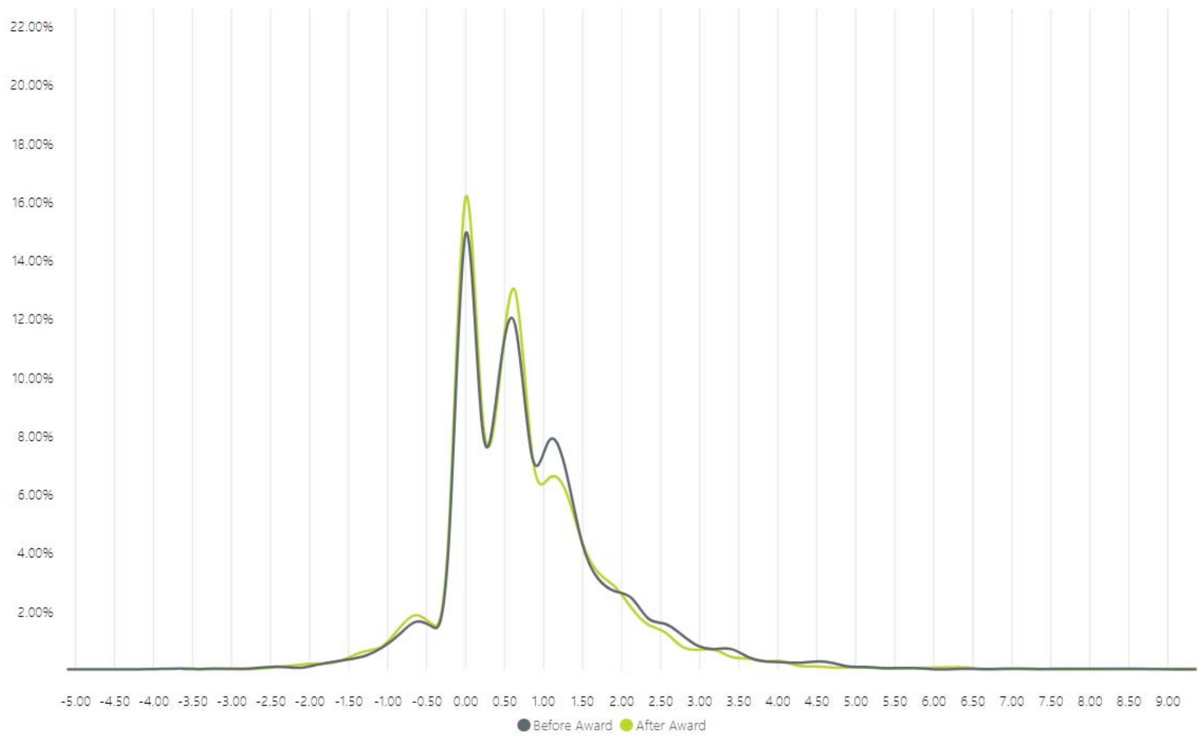
Appendix 1 – Script code

```python
# coding: utf-8

# In[ ]:


import requests
from bs4 import BeautifulSoup
import csv
import webbrowser
import io

def display(content, filename='output.html'):
    with open(filename, 'wb') as f:
        f.write(content)
        webbrowser.open(filename)

def get_soup(session, url, show=False):
    r = session.get(url)
    if show:
        display(r.content, 'temp.html')

    if r.status_code != 200: # not OK
        print('[get_soup] status code:', r.status_code)
    else:
        return BeautifulSoup(r.text, 'html.parser')

def post_soup(session, url, params, show=False):
    '''Read HTML from server and convert to Soup'''

    r = session.post(url, data=params)

    if show:
        display(r.content, 'temp.html')

    if r.status_code != 200: # not OK
        print('[post_soup] status code:', r.status_code)
    else:
        return BeautifulSoup(r.text, 'html.parser')

def scrape(url, lang='ALL'):

    # create session to keep all cookies (etc.) between requests
    session = requests.Session()

    session.headers.update({
        'User-Agent': 'Mozilla/5.0 (X11; Ubuntu; Linux x86_64; rv:57.0) Gecko/20100101 Firefox/57.0',
    })


    items = parse(session, url + '?filterLang=' + lang)

    return items

def parse(session, url):
    '''Get number of reviews and start getting subpages with reviews'''

    print('[parse] url:', url)

    soup = get_soup(session, url)

    if not soup:
        print('[parse] no soup:', url)
        return

    num_reviews = soup.find('span', class_='reviews_header_count').text # get text
    num_reviews = num_reviews[1:-1]
    num_reviews = num_reviews.replace(',', '')
    num_reviews = int(num_reviews) # convert text into integer
    print('[parse] num_reviews ALL:', num_reviews)

    url_template = url.replace('.html', '-or{}.html')
    print('[parse] url_template:', url_template)

    items = []

    offset = 0

    while(True):
        subpage_url = url_template.format(offset)

        subpage_items = parse_reviews(session, subpage_url)
        if not subpage_items:
            break

        items += subpage_items

        if len(subpage_items) < 10:
            break

        offset += 10

    return items

def get_reviews_ids(soup):

    items = soup.find_all('div', attrs={'data-reviewid': True})

    if items:
        reviews_ids = [x.attrs['data-reviewid'] for x in items][::2]
        print('[get_reviews_ids] data-reviewid:', reviews_ids)
        return reviews_ids

def get_more(session, reviews_ids):

    url = 'https://www.tripadvisor.com/OverlayWidgetAjax?
Mode=EXPANDED_HOTEL_REVIEWS_RESP&metaReferer=Hotel_Review'

    payload = {
        'reviews': ','.join(reviews_ids), # ie. "[illegible]",
        #'contextChoice': 'DETAIL_HR', # ???
        'widgetChoice': 'EXPANDED_HOTEL_REVIEW_HSX', # ???
        'haveJses': 'earlyRequireDefine,amdearly,global_error,long_lived_global,apg-Hotel_Review,apg-
Hotel_Review-in,bootstrap,desktop-rooms-guests-dust-en_US,responsive-calendar-templates-dust-
en_US,taevents',
        'haveCsses': 'apg-Hotel_Review-in',
        'Action': 'install',
    }

    soup = post_soup(session, url, payload)

    return soup

def parse_reviews(session, url):
    '''Get all reviews from one page'''

    print('[parse_reviews] url:', url)

    soup =  get_soup(session, url)

    if not soup:
        print('[parse_reviews] no soup:', url)
        return

    hotel_name = soup.find('h1', class_='ui_header h1').text

    reviews_ids = get_reviews_ids(soup)
    if not reviews_ids:
        return

    soup = get_more(session, reviews_ids)

    if not soup:
        print('[parse_reviews] no soup:', url)
        return

    items = []

    for idx, review in enumerate(soup.find_all('div', class_='reviewSelector')):

        badgets = review.find_all('span', class_='badgetext')
        if len(badgets) > 0:
            contributions = badgets[0].text
        else:
            contributions = '0'

        if len(badgets) > 1:
            helpful_vote = badgets[1].text
        else:
            helpful_vote = '0'
        user_loc = review.select_one('div.userLoc strong')
        if user_loc:
            user_loc = user_loc.text
        else:
            user_loc = ''

        bubble_rating = review.select_one('span.ui_bubble_rating')['class']
        bubble_rating = bubble_rating[1].split('_')[-1]
        bubble_rating = int(bubble_rating)/10

        item = {
            'restaurant_name': hotel_name,
            'review_body': review.find('p', class_='partial_entry').text,
            'review_date': review.find('span', class_='ratingDate')['title'], # 'ratingDate' instead of
'relativeDate'
            'rating': bubble_rating
        }

        items.append(item)
        print('\n--- review ---\n')
        for key,val in item.items():
            print(' ', key, ':', val)

    print()

    return items

def write_in_csv(items, filename='results.csv',
                  headers=['hotel name', 'review title', 'review body',
                           'review date', 'contributions', 'helpful vote',
                           'user name' , 'user location', 'rating'],
                  mode='w'):

    print('--- CSV ---')

    with io.open(filename, mode, encoding="utf-8") as csvfile:
        csv_file = csv.DictWriter(csvfile, headers)

        if mode == 'w':
            csv_file.writeheader()

        csv_file.writerows(items)

DB_COLUMN   = 'restaurant_name'
DB_COLUMN1 = 'review_body'
DB_COLUMN2 = 'review_date'
DB_COLUMN3 = 'rating'

start_urls = [
    'restaurant_url'
]

lang = 'en'

headers = [
    DB_COLUMN,
    DB_COLUMN1,
    DB_COLUMN2,
    DB_COLUMN3
]

for url in start_urls:

    # get all reviews for 'url' and 'lang'
    items = scrape(url, lang)

    if not items:
        print('No reviews')
    else:
        # write in CSV
        filename = url.split('Reviews-')[1][:-5] + '__' + lang
        print('filename:', filename)
        write_in_csv(items, filename + '.csv', headers, mode='w')
```

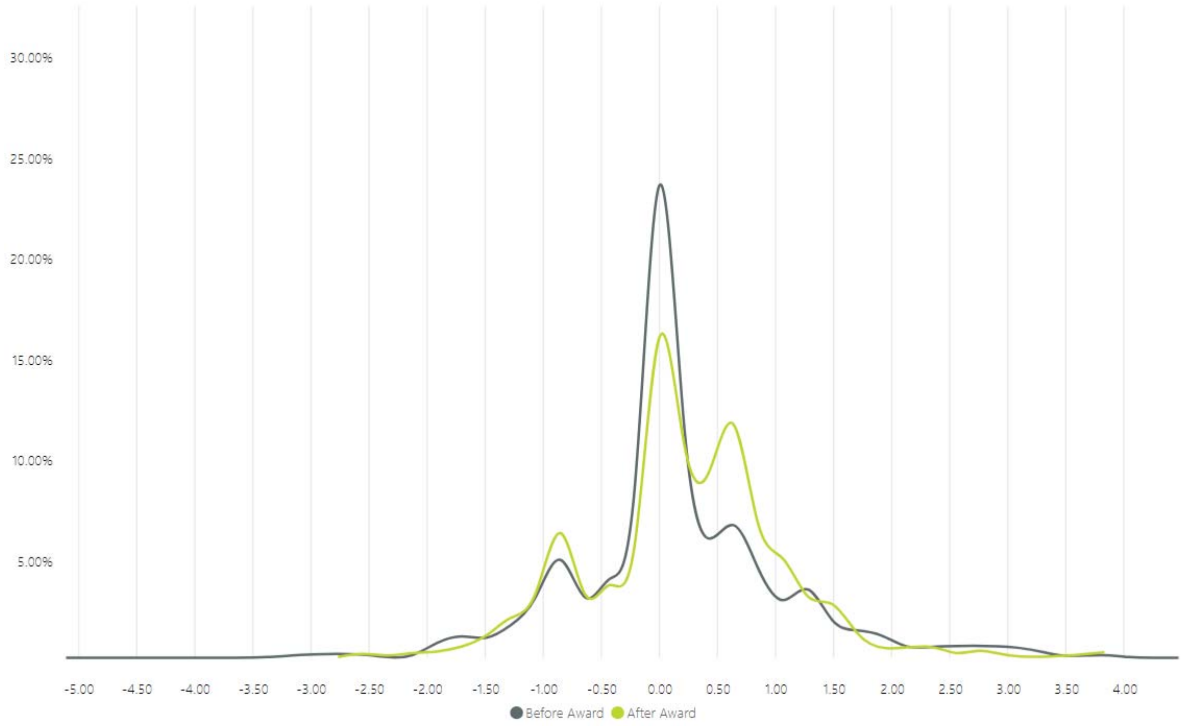
Appendix 2 - Sentiments around price before (grey) and after the award (green)



Appendix 3 - Distribution of sentiments before the award (grey) and after the award (green)



Appendix 4 – Distribution of sentiments around price before (grey) and after the award (green)



Appendix 5 – Distribution of reviews restaurant group