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CHARACTERISING SENTIMENT SPILL-OVER IN RESTAURANT REVIEWS

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Dissertation report presented as partial requirement for obtaining the Master’s degree in Information Management

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ABSTRACT

Usual restaurants' attributes such as menu price, cuisine type, and overall rating are key factors often considered by consumers when deciding to go out to eat. Such metrics are also largely explored by virtual communities, e.g. TripAdvisor, which allow users to rate restaurants and share their experience through online reviews. Such model raises the question whether sentiment spill-over occurs based on these features or, in other words, whether specific restaurant characteristics can influence or bias sentiment orientation. Using Network Analysis, online consumer reviews, and lexicon-based Sentiment Analysis this study presents an approach to identify whether restaurants with similar characteristics share similar sentiment orientation. Although results showed that it is possible to map sentiment orientation to restaurant characteristics, no evidence was found of a deterministic proxy between these features with sentiment orientation, meaning that the sentiment towards a restaurant is likely to be influenced by other factors rather than menu price, cuisine type or rating. In addition, the analysis showed that restaurants in Lisbon have an overall good rate and that the rates correlate positively with favourable sentiments for both Portuguese and English languages.

KEYWORDS

Restaurant eWOM; Sentiment Analysis; Network Analysis.

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1. Introduction

As an outcome of the Web 2.0 revolution consumers started taking several decisions grounded on virtual communities (e.g. where to go, who to trust or what to buy) modifying the relationship and structure in hospitality and tourism industry (Keates, 2007; Berman & Ragna, 2011). The interaction between consumers and services were deeply affected as the information created and read became more accessible due to the emergence of new connected devices (Ge, So, & Hudson, 2017). This shift resulted in novel social behaviours like, for example, the habit of reviewing online services that helps other users to be aware of previous faced situations. In this process of sharing an experience, consumers either rely in linguistic features, sentimental words, or rational explanations to express themselves online. Such richness of information in reviews made them a valuable commodity for the industry, offering insights that are capable to influence other's decisions, sales, or service patronage (Pan, McLaurin, & Crotts, 2007; Dellarocas, Xiaoquan, & Awad, 2007). Such commodity is called electronic word of mouth (eWOM).

The eWOM (Dellarocas, 2003) has its major effect on informing people. Customers and managers benefit from it when they wish for convenient data about services. On the one hand, consumers search in eWOM useful information to support their own decisions, which in this new environment is achieved through reading other users' perceptions and shared experiences (Archak, Ghose, & Ipeirotis, 2011; Filieri, Alguezaui, & McLeay, 2014; Forman, Ghose, & Wiesenfeld, 2008; Li & Hitt, 2008). On the other hand, managers can identify in eWOM business difficulties and new opportunities in the market (Pantelidis, 2010).

Generally, research has focused on understanding why customers engage on eWOM in hospitality and tourism markets (Dellarocas, 2003; Filieri, Alguezaui, & McLeay, 2014), the resources that eWOM can offer (Pan, McLaurin, & Crotts, 2007; Filieri, Alguezaui, & McLeay, 2014; Erkan & Evans, 2016) or why customers rely on eWOM (Kim, Mattila, & Baloglu, 2011). Particularly for restaurants, previous studies showed that the eWOM importance relies on accessing local and specific knowledge, either by reading previous opinions or experiences about eateries, that help to decrease uncertainties about restaurant services (Mangold et al. 1999; Litvin et al., 2008). Although most of the research done in the restaurant industry addressed eWOM causes and effects on sales and patronization, or in understanding key factors of customer satisfaction, few studies analysed the human sentiment embedded on these factors (Schuckert, Liu, Law,

2015) or the causes for different sentiments toward restaurants. Even fewer studies analysed sentiments in networks, another kind of technology that became popular because of Facebook. The gap in the literature in understanding sentiments embedded in eWOM can be explained by the advancements of such technologies and tools that now allow this kind of analysis on eWOM and, of course, by the general consumer adoption of virtual communities (Pallavicinia, Cipressob, Mantovania, 2016). Therefore, today's data and methods permit a new form of analysis that merge different kinds of technologies together which are capable of supplying insights or hidden interconnections.

With that in mind, the current study used customer experience attributes found in existing research and analysed them under the sentiment perspective, using networks. The use of graphs and networks with Sentiment Analysis can be considerably important as Sentiment Analysis alone is considered a quality metric (Pang, Lee, 2008) and presents limitations in grasping contexts – i.e. purely text data does not consider or reflect the networks that occurs in real life situations (Pallavicini, Cipresto, Mantovani, 2016). Consequently, an interesting research path to follow is to try to unfold these complex relationships between sentiments and restaurants attributes using graphs. For the restaurant industry, the results of such approach can reveal important insights under distinct perspectives (Pantelidis, 2010) or identify how sentiments vary according to different aspects of restaurants (Levy, Duan, & Boo, 2013; Jurafsky, Chahuneau, Routledge, & Smith, 2014).

Therefore, this study investigated the following question: "Does our sentiment towards a restaurant spills-over to others based on specific characteristics?". The main idea was to explore whether the characteristics of restaurants can be a proxy to sentiment orientations. For example, does an overall positive evaluated, and low-priced Portuguese restaurant shows the same sentiment changes as others positively evaluated, and low-priced, Portuguese restaurants?

To accomplish the desired goal, TripAdvisor online reviews were collected and used to compute sentiment scores for the restaurants. Restaurants were grouped together by similar variation of sentiment in time and then a graph of restaurants was built on top of the results, examining which restaurants were neighbours in the network. The goal was to identify whether restaurants that had the same variations in time, and that were neighbours in the network, also shared the same characteristics.

This study is organized as follows: Topic 2 lists relevant literature research related to eWOM, Sentiment Analysis and Network Analysis. Topic 3 explains the data collection, the sentiment analysis technique used and how the network was built. Topic 4 contains three subtopics and explores the results of the study. The first subtopic presents the restaurants as datapoints and shows some statistics in this dataset. The second subtopic investigates the reviews as datapoints and shows the resulting polarization score in a time series. The last subtopic presents the resulting network and shows the results of the network analysis. Topic 5 discusses the results. Topic 6 explores the research contributions and managerial implications, study limitations and suggestions for future research.

2. Literature Review and Research Hypotheses

2.1. EWOM in the restaurant Industry

Managers in the restaurant industry value word of mouth and often try to keep an eye on what customers say about their establishments. Traditionally, word of mouth was geographic limited and frequently restricted by physical boundaries of communication. However, with the Internet advancements, word-of-mouth has transcended this format and scaled up to many individuals (Avery et al. 1999), becoming a critical commodity for restaurants. Another change is observed in the general adoption of Web 2.0 communities, rather than conventional restaurant connoisseurs and specialist's magazines like *Michelin Guide* and *Gault Mila*, among amateurs or dilettantes This democratization of opinion-making and service evaluation allowed the emergence of many opinion pools, such as TripAdvisor, Zomato and Yelp.

Hennig-Thurau et al. (2004) define eWOM as "*any positive or negative statement made by potential, actual, or former customers about a product or company, which is made available to a multitude of people and institutions via the Internet"*. Under this perspective, one can consider a restaurant online review as result of dining events that are described online to other users referring to an earlier contact with a specific experience.

Studies investigating eWOM on restaurants virtual communities make evidence of the user's perception of this type of information as credible, useful, and trustworthy (Filieri, Alguezaui, & McLeay, 2015; Erkan & Evans, 2016) that is independent from brand advertisement (Forman, Ghose, & Wiesenfeld, 2008; Zhang, Ye, Law & Li, 2010; Tai-Yee Wu & Carolyn, 2016). Moreover, channels of eWOM represent low-cost and easy means to access insights both to managers - in identifying main attributes present about their business (Pan, McLaurin, & Crotts, 2007; Pantedilis, 2010) - and to customers

- in allowing them to get important pre-information for purchase decisions which affects choices and potential outcomes (Chevalier & Mayzlin, 2006; Cheung & Lee, 2008; Cheung & Thandani, 2012).

Xiang and Gretzel (2010) showed that consumer-based websites are an important pool of opinions and stated that this kind of information source was present in 27% on different search engines at the time. Because of the importance of such content in consumer decision making process, a concerning about the genuineness and fake content started to appear (Keates, 2007; Morrison, 2012). O'Connor (2010) explored these issues and found that allegations of illegitimate reviews were groundless, particularly claiming that TripAdvisor platform was a good source of information for academic and business purposes. More recently, TripAdvisor Transparent report also asserts that only 2% of the present reviews are not authentic (TripAdvisor Review Transparency Report, 2019).

2.2. Restaurant Customer Satisfaction

Many researchers named common fundamental attributes contributing to consumer's dining experience, namely food, price, ambience, and service (Andaleeb, & Conway, 2006; Ryu, & Han, 2010; Pantelidis, 2010; Zhang, Zhang, & Law, 2014; Qiwei, Bo, Yang, & Lei, 2016). Empirical studies point to a top-three ranked attributes that are strongly correlated in patronising customers, like food quality, atmosphere, and service. These can predict consumer satisfaction and intention to return to a restaurant (Mattila, 2001; Ryu & Han, 2010). Kivela, Inbakan, and Reece (2000) found a positive correlation between willingness to return to a restaurant and satisfaction of expectations, although the study did not mention word of mouth. Zhang, Ye, Law, and Li (2010) investigated that consumer-generated ratings about ambience, service, and food quality as well as the volume of reviews were positively related to the popularity of restaurants in China.

Although there are common attributes related to dining satisfaction in all those studies, setting up a hierarchy about them is yet inconclusive. Andaleeb and Conway (2006) study suggested that service quality, price, and food, in that order, would lead to the satisfaction of customers in a restaurant. Furthermore, Gupta, McLaughlin, and Gomez (2007) stated that the order of significance considered by customers was food quality, price, greeting and service. Exploring further relevant attributes in the hierarchy propositions, Gan et al. (2017) introduced context as a new attribute, since consumers are those who create the meaning and the value of an experience summed up with the stimulus received by products and services to get a final evaluation of their experiences (Hosany & Gilbert, 2009; Prahalad & Ramaswamy, 2003). For Gan et al. (2017) the order should be food, service, context, price, and ambience.

Context, in particular, is very important when considering a good experience since it is capable of biasing events in distinct ways. Nowadays, dining also embeds different meanings – some examples being work meetings, dates, and eating out with family or friends. Zaltman, Olson, & Forr (2015) acknowledged the importance of context in enhancing consumers emotion experiences, suggesting that hospitality managers should carefully elaborate meanings to different contexts. Most of the platforms in this area, such as Yelp and TripAdvisor, recognize its importance as they already employ links on their website, such as "Good for…", and make clear the expected price on the restaurant page, as well as the type of cuisine, number of reviews and other characteristics.

2.3. Sentiment Analysis in Restaurant industry

Sentiment Analysis is perhaps the most popular research field of Natural Language Processing (NLP) focusing on evaluating people's opinions, sentiments, or emotions. More specifically, it is the analysis of people's opinions toward entities (e.g., products, services, or organizations) and their aspects (e.g., colour, taste, cost) through text analysis. In a broad sense, sentiment analysis aims to identify positive and negative explicit, or implicit, opinions within written text or to predict the document polarization in a strength-range value (Pang & Lee, 2008). Sentiment Analysis can be done in three main levels of analysis: document-level, sentence-level, and aspect-level. Document-level sentiment analysis is specially applied to online reviews (Calheiros et al., 2017; Liu, 2015; Moro et al., 2019b) because it simplifies the tasks of identifying the opinionated entity, the target, and the author. Consequently, this is the level of analysis chosen in many other studies (Qiwei, Bo, Yang, Lei, 2016; Guerreiro & Rita, 2020; Nave et al., 2018; Yu et al., 2021) and was used in this study. This kind of analysis is the easiest of the three levels because assumes that a review generally refers to a target (i.e., a restaurant) and an aspect (more generally the food, service, or price, but still they refer to the restaurant as a whole) and is authored by some reviewer (it has just one author per review, differently from blogs or forum discussions, where many reviewers exist).

There is an extensive literature about sentiment analysis and its techniques applied to sales but, curiously, its use in tourism and hospitality industry related to restaurants is still sparse. Schuckert, Liu, & Law (2015) reported that among fifty relevant articles containing online reviews and main branches of hospitality and tourism industry (e.g., hotel, travel, sites) only 18% contemplated restaurant and opinions. Interesting research in restaurant industry and sentiment analysis includes the study by Kang, Yoo & Han (2012) which proposed an enhanced Naïve Bayes version to evaluate restaurant online reviews and solved the different accuracy problem that Naïve Bayes showed for positive and negative reviews, technically addressed as unbalanced dataset. Zaltman, Olson, & Forr (2015) examined the influence of review attributes and sentiments on restaurant star rating. Yu et al., (2021) applied Support Vector Machine (SVM) and word frequency to decipher sentiment tendency of each restaurant review as an innovative method to find different features for different types of cuisine. Lastly, the study by Chaves et al. (2014) involved Lisbon and the Algarve regions, and captured the most relevant aspects of the restaurant industry locally.

Different approaches of sentiment analysis lead to different desired results. One kind of Sentiment Analysis technique that aims to quantify the sentiment strength or polarity is called lexicon-based Sentiment Analysis (Liu, 2015). Its main idea is to understand how much negative or positive a sentiment is for a specific document using a dictionary that maps word to weights. This method is known as lexicon approach because relies in a series of meanings behind the word uses, knowledgeable databases (or dictionaries) of semantic values, or ontologies to quantify sentiments. O'Connor et al. (2010) used this approach and computed the total sum of opinionated words (e.g., great, cool, horrible) finding very interesting results. The simplest lexicon-based approach is to count positive and negative words, which results in an overall value. Table 1 lists some popular dictionaries used for lexicon-based sentiment.

2.4. Network Analysis in Restaurant industry

Network Analysis refers to the study of entities and how they interact with each other. Prior investigation of such relationship's dates to the 1930s (Moreno, 1934) and focused mainly in understanding social interactions. After this study, as this kind of analysis wasapplied in a broad range of topics using sociograms of different groups and entities as its core engine, the term Social Network Analysis was set (Barnes, 1954). Otte and Rousseau (2002) describe the social network as a wide-ranging scheme for exploring

Table 1 - Popular Sentiment Lexicons dictionaries

Name	Paper
AFINN Lexicon	Nielsen, 2011
Bing Liu's lexicon	Minqing & Bing 2004
General Inquirer	Stone et al, 1966
VADER lexicon	Hutto & Gilbert, 2015
SentiWordNet	Baccianella, Esuli & Sebastiani, 2010
Sentilex-pt	Carvallho & Silva, 2015

social structures, but one notable definition is the one by Wetherell et al. (1994), that describes SNA as follows:

"Most broadly, social network analysis (1) conceptualises social structure as a network with ties connecting members and channelling resources, (2) focuses on the characteristics of ties rather than on the characteristics of the individual members, and (3) view communities as 'personal communities', that is, as networks of individual relations that people foster, maintain, and use in the course of their daily lives.".

Nowadays, since many areas use social network analysis and some of the entities within the studies do not rely on social units, a new term called Complex Network Analysis was coined (Strogatz, 2001). In a nutshell, network analysis is another way of organizing and representing data apart from the tabular form, being the entities - nodes or vertices – and the relationships – named as edges - the two most important network elements. Graphically, a network is usually composed of circles and lines. The circles refer to the nodes and the lines refer to the edges that connect two nodes. One of the advantages of network analysis is that they can be understood graphically and can reveal contextual and hidden ties. In the analysis of networks, the graphs can be classified as egocentric or sociocentric, and its characteristics have range of definitions such as weighted, signed, or symmetric.

In hospitality and tourism literature, the use of the network analysis is still recent. Casanueva, Gallego, and Garcia-Sanchez (2014) paper examines 23 distinct relevant studies that appeared in the 2013 Thompson Reuters Journal Citation Report in the section about Hospitality, Leisure, Sport & Tourism. The results also showed that most of the research consist in the analysis of tourism destinations and clusters, or ties between stakeholders - firms from different tourism sectors, non-business organizations, government studies, etc – noticing that most of published articles date to the period of 2008 to 2013. As the time of this writing, it was difficult to find studies that relate sentiment analysis, restaurant industry and network analysis.

The study of networks altogether with other kinds of analysis – e.g. Sentiment Analysis - can unveil different outcomes as stated by Pallavicinia, Cipressob, & Mantovania, (2016) - the analysis in text data alone results in a limited approach without considering the relationships and networks amongst user's and other factors. Collecting and analysing textual data without taking into consideration possible links and connections that may exist can put away important insights and reduce exploratory value.

2.5. Hypotheses Development

As the eWOM plays a significant role in a success of a restaurant, and it is capable of influence others in unrelated and unexpected factors, there is a chance that a bias exists in our evaluations that motivate us without we are explicitly aware. Following this line of thinking, and considering that eWOM also plays an important role in building consumer trust toward a success of a business, many studies investigated diverse elements and attributes that affected online customer evaluation on services. Some examples are post-transaction issues (Qu, Zhang & Li, 2008), amount of information of customer's expertise (Park & Kim, 2009), or type of media used (Piccoli & Ott, 2014). Other studies focused on the impact of different attributes such as food, physical environment, or service, as the proxy to satisfaction or ratings in restaurants (Zhang, Zhang, & Law, 2012; Zhang, Zhang, & Law, 2014).

In a way to complement previous research, one interesting line to go along is to understand how sentiments are built on and how they relate to restaurant characteristics. To capture such variations, a network was built to verify whether the relationship between sentiments and restaurants characteristics were arbitrary. Such network relied in implicit relationships, that is, in similar attributes that occurred together between restaurants. To test these inferences and evaluate the significance about the randomness of the connections, the link between two restaurants was based on the number of similar variations of sentiment in time. The network only considered ties that were statistically significant with ϕ-correlations and t-test. The inferential hypotheses that check the randomness of sentiment to restaurant characteristics are the following:

$H_{0\text{-}A}$: *The sentiment orientation for restaurants vary according to the price. In other words, groups of restaurants that are similar in terms of sentiment variation in time also share similar menu prices.*

$H_{0\text{-}B}$: *The sentiment orientation for restaurants vary according to the rate. In other words, groups of restaurants that are similar in terms of sentiment variation in time also share similar rates.*

$H_{0\text{-}C}$: *The sentiment orientation for restaurants vary according to the type of cuisine. In other words, groups of restaurants that are similar in terms of sentiment variation in time also share common cuisine types.*

The hypotheses were tested by contradiction, meaning that the tests were done comparing the original network of Lisbon restaurants with a randomly distributed network, verifying whether the distributions of sentiments per restaurant characteristics were arbitrary. The expected behaviour was that two restaurants that had similar sentiment orientations, would also share similar characteristics, for example, that establishments with similar cuisine type had similar sentiment orientation or that establishments with similar rates had similar sentiment orientation.

These hypotheses, if rejected, can help to answer questions like: “Is the restaurant type of cuisine a factor that can bias sentiments?” or “If I focus on X or Y characteristics for a restaurant, will I get some advantage in the marketplace?”. If such aspects affect or bias sentiment orientation deterministically (e.g., not randomly), this approach is expected to capture such phenomenon as a way for to apply them strategically in the future.

3. Methodology

This section presents the data collection, the sentiment analysis, and the network analysis used. It begins presenting the dataset variables that were retrieved from the web and data cleansing. Then, details the sentiment analysis, explaining the technique chosen for the computation of the sentiment score. It also explains the underlying matrix preparation, the ϕ-correlation and the t-statistic that was applied on the network.

3.1. Data collection

The data used in this study were retrieved from the TripAdvisor website, which is a web platform designed explicitly to present services to the users with a consumer review approach. TripAdvisor website was selected for three main reasons. First, TripAdvisor is a popular source of information and is one of the biggest websites offering tourism services nowadays. At the time of this writing, the website counted a total of 795 million reviews and opinions, and 8.4 million accommodations, airlines, experiences, and restaurants (About TripAdvisor, 2019). Second, TripAdvisor asks for a valid registration email address for users and only allows registered members to rate by filling a website form. When reviewing a restaurant, users can write in plain text a review and give a numeric rate. When asked for the rate, members need to report values in the range of 1 to 5 (each one corresponding to terrible, poor, average, very good and excellent) based on the overall food, service, price, and atmosphere. The rates of all reviews are succinctly summarized by the TripAdvisor algorithm resulting in an aggregated valence that allows easy collection. Third, TripAdvisor is commonly assumed to be a good source for studies of this kind (O'Connor, 2010; Moro et al., 2019a; Tiago et al., 2020) and is very popular among enthusiastic restaurateurs that like to put their opinions and share distinct experiences.

The data was retrieved by an automated Python script that accessed and parsed HyperText Markup Language pages available in TripAdvisor website. The script traversed only this single domain by a pattern that included Lisbon's restaurants, saving the data to a CSV file and to a MySQL database. The dataset contains the following fields:

- **Restaurant title:** the ID of the restaurant.

- **Aggregated rate:** the aggregated rate of the restaurant, calculated by TripAdvisor algorithm.
- **Restaurant total of reviews:** the total number of reviews a restaurant receives.
- **Restaurant rank:** the rank of the restaurant, calculated by the TripAdvisor algorithm.
- **Restaurant price level range:** the restaurant price level in currency symbols. The symbol can have the following values: €, €€-€€€ and, €€€€. It is a piece of information detailed by the owner of the page.
- **Restaurant price range:** the restaurant numeric price range of a restaurant which is presented in the form of 5€-10€, 20€-30€, and so on. It is a piece of information detailed by the owner of the page.
- **Certificate**: a Boolean variable that indicates whether a restaurant page has a TripAdvisor certificate of excellence.
- **Features**: a list of strings that describes the features of a restaurant such as type of cuisine (e.g. Portuguese, Indian, Seafood), dietary information (e.g. vegan, gluten-free) or whether the restaurant has other attributes such as drinks, parking or music.
- **Longitude and latitude:** the geocode derived from an address using google maps API.
- **Reviewer ID:** the ID of the reviewer.
- **Review location**: the location registered in the reviewer's profile.
- **Reviewer contribution**: the total of reviews given by a customer so far.
- **Review helpful votes**: the number of likes that a review received by other reviewers.
- **Review rate**: the rate of each review.
- **Review title**: the title of each review.
- **Review content**: the content of each review.
- **Review date**: the publish date of the review.

The initial dataset had a total of 4,380 restaurants. The download was done in December 2019 and collected all available reviews in the TripAdvisor website since 2007. The restaurants available in the dataset were the ones that have a restaurant classification in the establishment type, hence other kinds such as cafes or bars were not collected.

Some analyses were done to guarantee data quality, like verifying whether rates were available or whether the reviews were complete or just partially gathered. Only reviews with utf-8 encoding were considered in the text analysis. Only restaurants that have English and Portuguese reviews were then selected, resulting in a data sample of 3,735 restaurants. To limit the number of reviews per entity, only restaurants with a minimum of 5 reviews and a maximum of 1,500 reviews were chosen. The final dataset consisted of 3,285 restaurants, with a total of 165,454 reviews in English and 137,726 reviews in Portuguese.

3.2. Sentiment Analysis

For text analysis, the NLTK Python's Library (Bird et al. 2009) was used. The first step consisted in creating a Corpus of documents that was saved into disk. Then, using the NLTK API, the documents were retrieved and loaded into memory for processing. The pipeline to transform raw text into tokens was the same presented by Bird et al. (2009). Punctuations and stop words were not removed.

To evaluate the sentiment scores per review a similar approach to O'Connor et al. (2010) was adopted, being the sentiment orientation based on a value of opinionated and semantical words such as great, cool, horrible, or nightmare. Words without semantic meaning were attributed a value of zero. For the English language, the AFINN lexicon (Nielsen, 2011) was used to give a numerical value to words. The AFINN lexicon was selected because contains internet slangs and strong obscene words commonly used among reviewers. This dictionary was created by the author and has a total of 2,477 unique tokens. It relies only on the word's valence in the range of -5 to +5 - very negative to very positive - and leaves out subjectivity or objectivity analysis and rules of negation. For Portuguese reviews, the SentiLex-PT-02 lexicon vocabulary was used. This lexicon was chosen because it is especially useful for sentiment score computations and contains a considerable number of different tokens and its sentiment scores. This lexicon is made up of 7,014 lemmas and 82,347 inflected terms (Carvallho & Silva, 2015). The SentiLex-PT-02 scores +1 for positive words, -1 for negative words, and 0 for neutral words.

The process to calculate the sentiment orientation per restaurant was the following. First, for each restaurant ID, all the reviews had to pass through an operation that assigned values to the words. To compare the Portuguese and English results, the values were standardized in advance. Then, the reviews were averaged monthly (for days or weeks the results presented several null values, and they were not considered in further analyses). This resulted in a data structure with the restaurant ID as rows and a vector of sentiment orientation values per month as columns. The final processing grouped the scores into intervals of quarters using an exponentially weighted moving average, or EWMA (Zangari, 1994), such that every value of a quarter is the exponentially weighed moving average over the sentiment scores per month (e.g., the average scores for January, February, and March). In other words, the sentiment value of a quarter was calculated with a span of 4, so that the most recent month weighted more. EWMA presents two advantages over simple moving average. First, the most recent value has the highest weight and the weights for the previous values drop off exponentially (this follows an assumption that recent evaluations counts more). Second, the implementation in Python handles missing values better.

Besides the orientation strength calculation, a two class-label approach was used to classify the reviews into positive and negative labels. A review was considered positive if it had a rate greater or equal than 3, and negative otherwise. The resolution to include the rates with value 3 into positive class was due to the positive bias for neutral words in online reviews as observed in Taboada et al. (2011). The performance of the lexicon-based approach was evaluated by the Accuracy, Precision, Recall and F1-score scores, measured for each review by its orientation score (positive if the total sum of lexicon words is higher or equal than 0, and negative otherwise).

3.3. Network Analysis

For the network construction, a Python library called NetworkX was used. NetworkX is package for creation, manipulation and study of the structure, dynamics, and functions of complex networks. The input of a graphic network is generally represented in a matrix form. The one used in this study for the restaurants network was a matrix with a restaurant-by-restaurant domain whose cell of the matrix was a value that indicated the number of similar sentiment variation in time. Two restaurants were considered to have the same variation in time if both presented a positive, or negative, sentiment variation compared to a previous quarter.

The resultant matrix only considered statistically significant links with respect to restaurants' sentiment co-variation - this procedure was adopted in the literature for other topics (Ronen et. al, 2014; Candia, Encarnação, & Pinheiro, 2019). The statistically significant connection is given by the probability of finding a connection between restaurants that is larger than the prevalence of two restaurants alone, meaning, in other words, that P(*i*,*j*) > P(*i*)P(*j*). To get these links a ϕ-correlation method was used to calculate the tie strength of two restaurants, filtering out through a t-statistical test links that occurred by random chance and links that had negative ϕ-correlation.

The final matrix, M_{ij}, was the matrix representing the number of common co-variations in time for a restaurant *i* to restaurant *j*. The correlation ϕ_{ij} between restaurants *i* and *j* was given by:

$$\boldsymbol{\phi_{ij} = \frac{M_{ij}N - M_i M_j}{\sqrt{M_i M_j (N - M_i)(N - M_j)}}}$$

Where M_i represents the number of similar sentiment variation of restaurant i ($M_i = \sum_j M_{ij}$) and N represents the total number of co-occurrences in the dataset. ϕ_{ij} was positive for pairs of restaurants whose similar sentiment variation occurred more often than their representation alone and was negative otherwise. The statistical significance of the correlations of matrix M was calculated by the t-statistic:

$$\boldsymbol{t_{ij} = \frac{\phi_{ij}\sqrt{D-2}}{\sqrt{1-\phi_{ij}^2}}}$$

Where $D - 2$ represents the degrees of freedom of the correlation, with $D = \max(M_i, M_j)$. The final network only considered links that were statistically significant with P < 0.05 ($t_{ij} > 2.021$ for $D > 40$; one tailed) and nonnegative ϕ-correaltion greater than zero.

4. Results

4.1. Restaurant Dataset - Exploratory Data Analysis

Table 2 presents some summary statistics of the restaurant dataset. One noticeably statistic of this dataset was that Portuguese and English alone had most of the reviews and summed up to 58% of the total count. It can also be seen that the restaurants had a mean of 157 reviews. The average level price range was 2.5, meaning that most of the restaurants characterized themselves as mid-range price and almost one third, or 32 %, of restaurants had a TripAdvisor certification.

Table 2 - Descriptive Statistics of Variables

Variable	N	Min.	Max.	Mean	Median	Mode	Std. Deviation
Rate	3285	1.000	5.000	4.076	4.000	4.500	0.619
Review Count	3285	5.000	1500	157.632	55.000	5.000	243.272
Certificate	3285	0.000	1.00	0.322	-	0.000	-
Price Range	1308	2.500	258.5	25.005	16.000	15.00	16.767
Price Symbol	3062	1.000	4.000	2.099	2.500	2.500	0.773
Pt. Reviews*	3285	1.000	657.000	41.924	17.000	4.000	66.165
Eng. Reviews*	3285	1.000	694.000	50.366	15.000	2.000	88.122

* Refers to each restaurant as a datapoint. Pt. Reviews means, for instance, that on average, a restaurant has 41 reviews in Portuguese. Do not confound with pt. reviews in topic 4.2, in which each review is a datapoint.

4.1.1. Restaurants Location

The restaurants addresses were transformed into latitude and longitude geocodes representation using Google Maps API. Note that this process resulted in only approximations geocodes according to the addresses that were reported on the restaurants webpages. Figure 1 shows the sample's restaurants distributions on the Lisbon map. The figure shows that restaurants were spread all over the city, with a concentration in the city centre or in touristic regions. Two of the latter regions were near Parque das Nações and near Torre de Belém – the regions signalled on the map extremes. The former region was located near the coast and distributed throughout the city. The areas that did not show any point refer to city parks, other establishments, or venues and were not show in the figure to easy the visualization.

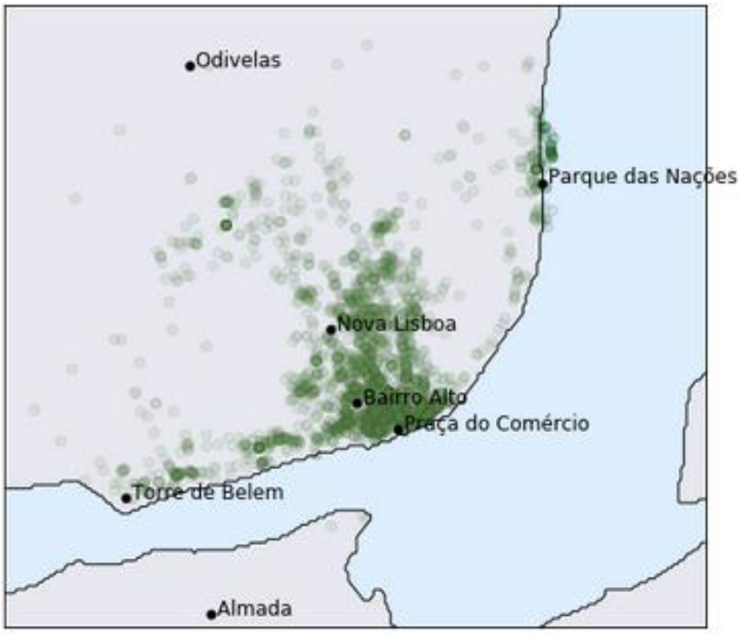

Figure 1 - Distribution of restaurants in Lisbon city

4.1.2. Restaurants Activity

Figure 2 plots the frequencies and probability mass function of the latest English and Portuguese review published by year, for each restaurant. According to the histogram distribution, 1,417 English and 1,342 Portuguese reviews were given in 2019, being the majority in number and representing 63% and 64%, respectively.

Though most of the reviews were given in 2019, a reasonable quantity accounted for previous years - 37% for English and 36% for Portuguese. One intuitive thought was that if a restaurant was available online it was assumed to be operating but, contrasting this perception, it was possible to see that some restaurants had the last reviews far from 2019 - some had it in 2013 and even in 2011.

For some reason, TripAdvisor did not remove them from the website until the data were collected. An interesting point to note is that the distributions of the reviews for both languages were very similar and followed the same pattern.

Figure 3, on the other hand, plots the distribution of the first review's year a restaurant had, for both English and Portuguese languages. The distributions showed that English reviews started earlier than Portuguese reviews and were higher in frequency per year compared to Portuguese reviews until 2011. In 2014, however, Portuguese reviews became more frequent reaching a peak in 2014. For both languages, after 2014 the number of reviews started to decrease. The first review's year for both languages started in 2007 and this is curious to note because the launch date of TripAdvisor was in 2000. It was impossible to know whether reviews were maintained since the beginning or if they were removed by the TripAdvisor website as this information was not disclose by the company.

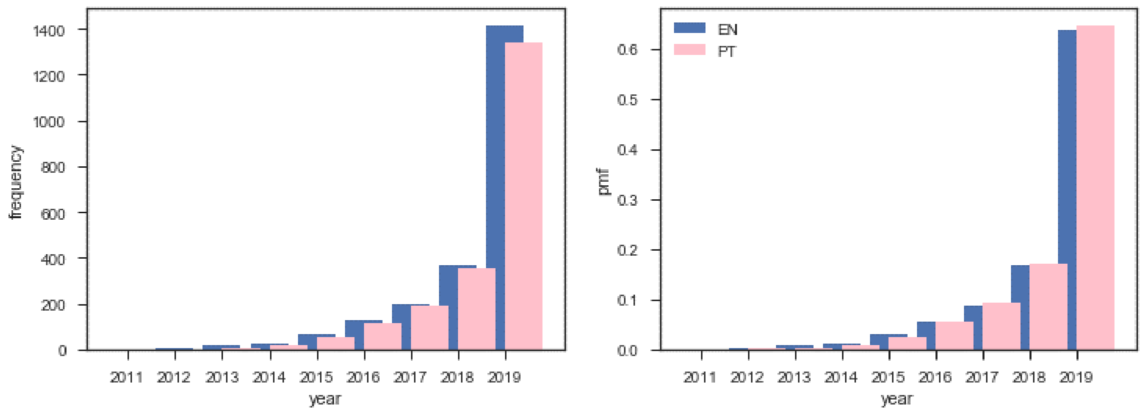

Figure 2 - Latest reviews by year for Portuguese (pink) and English (blue) reviews. Histogram of frequency (left) and probability mass function (right).

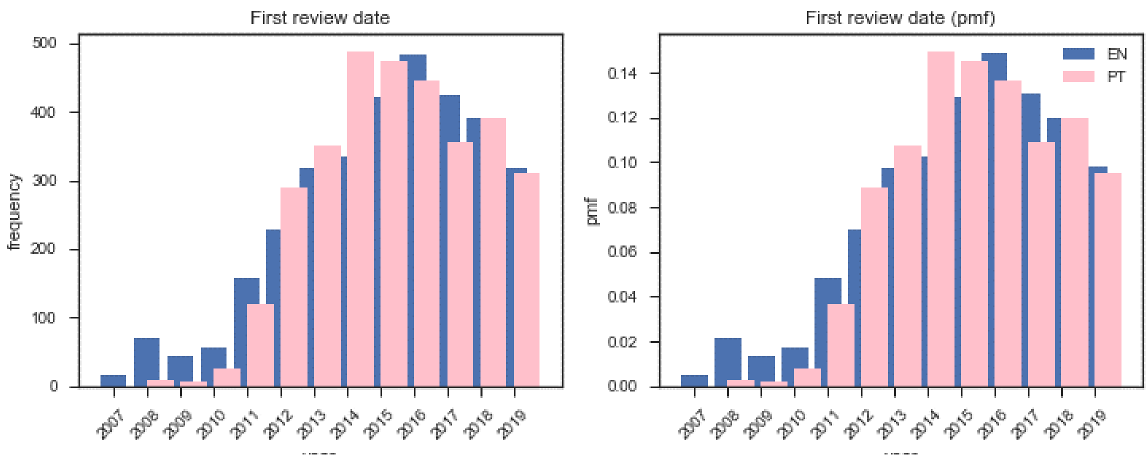

Figure 3 - First Portuguese and English reviews by year. Histogram of frequency (left) and probability mass function (right)

4.1.3. Restaurants Features

The TripAdvisor made available many distinct kinds of characteristics for a restaurant to tag itself. Some of them were presented in this topic and were commented. Other features were not considered much relevant can be found on the appendix B. Refer to it for a brief statistic of different types of restaurant features found on the dataset.

a. Restaurant Cuisine Type

There were 652 different cuisine types in the dataset, being a type of any possible value of 97 unique categories. The most popular type was “European”, “Portuguese” and “Mediterranean”, definitely because of the region of the study. These top three values alone stood for 59% of all 97 kinds available in the dataset. Figure 4 emphasizes this biased prevalence in a window plot, where the rows were the types of cuisine - in lexicographical order - and the columns each restaurant id.

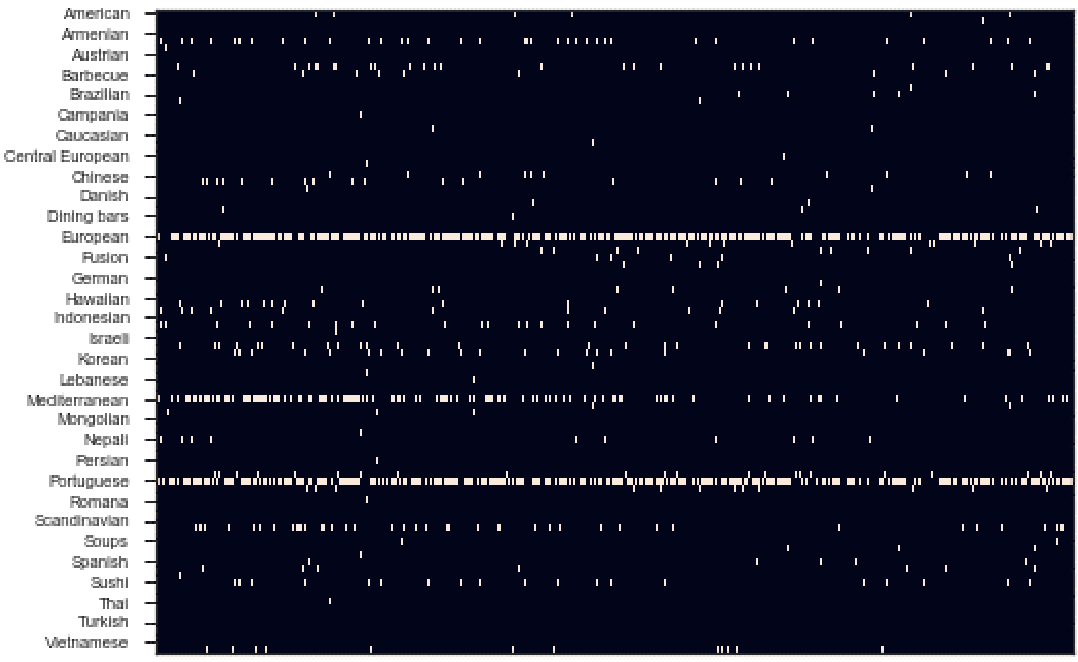

Figure 4 - Cuisine type matrix in a window figure. X-axis: restaurant's id. Y-axis: type of cuisine. White point indicates that ID has a specific type of cuisine, black coloured otherwise.

The white points in the matrix means that a specific type of cuisine was marked for a restaurant id. In the figure, it was possible to see three lines that “cut” the window horizontally - these were the most common types referred earlier. Table 3 lists the top six common cuisine types. From the table and figure altogether, it was possible to spot an Asian cuisine influence, particularly the Chinese, Japanese and Indian types.

Table 3 - Top six data cuisine type in decreasing order.

Cuisine type	N	%
European	2116	24.4
Portuguese	2085	24.1
Mediterranean	908	10.4
Seafood	260	3.0
Asian	236	2.7
Italian	231	2.6

Table 4, on the other hand, lists the top five co-occurrences cuisine types. As stated previously, the most overlapping types were “European, Portuguese” and “European, Portuguese, Mediterranean”. Table 4 also supports the presence of “Asian” culinary type, as well as “Japanese”.

Table 4 - Top five co-occurrences of cuisine types.

Co-occurrence cuisine types	N
European, Portuguese	730
European, Mediterranean, Portuguese	384
European, Mediterranean, Portuguese, Seafood	125
Asian, Japanese, Sushi	59
European	44

* 218 restaurants types unavailable was unavailable.

Figure 5 plots the co-occurrence matrix of cuisines types that appeared at least 3 times together, ordered by frequency. The colourful part of the matrix was denser in the “European”, “Portuguese” and “Mediterranean” columns, which appeared with a variety of different combinations. The “European” type, for instance, had some unexpected mixtures as “Brazilian” or “Indian”, but appeared with a relevant frequency with other more general kinds, such as “Pub” and “Pizza”. It was possible to see common relations as “Contemporary” and “Sushi” and “Barbecue”, “Brazilian”, “Steakhouse” and “Grill”. Half of the matrix was left blank because the matrix is symmetric.

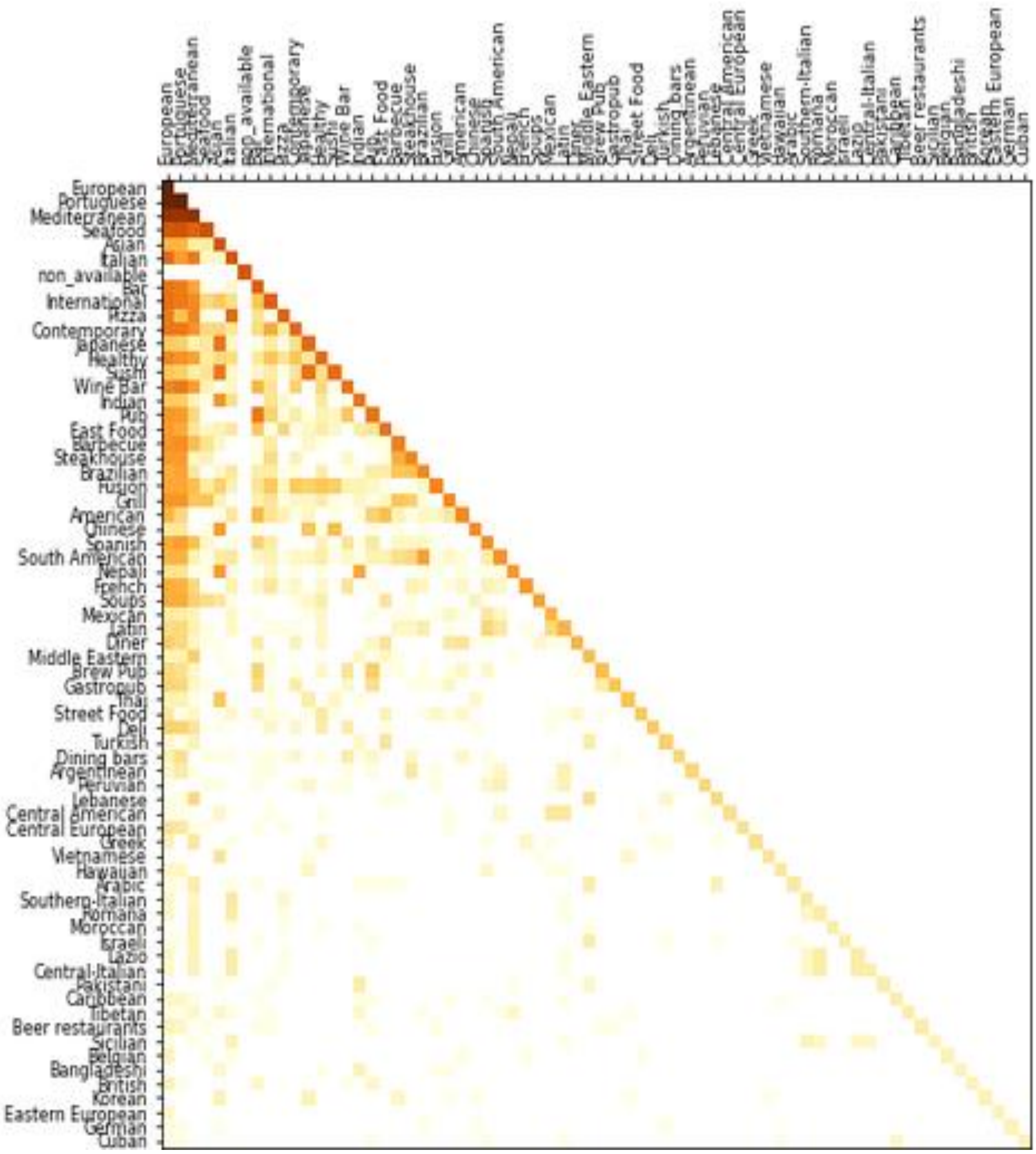

Figure 5 - Co-occurrence cuisine type matrix. Dark orange points show frequent co-occurrences. White points show that the co-occurrence does not exist.

b. Restaurant Rate

Figure 6 shows a histogram and a probability mass function of the restaurant rate attribute. The plot in the left shows that the mode of the distribution was 4.5 with 1,131 of frequency, followed by 4.0 with 1,057 counts. The plot in the right shows that those two rates stood for 66.6% of all distinct values. As the plots show, TripAdvisor website algorithm round the overall rates by 0.5 points. What was notable was that there were much more positive ratings like 4.0s and 5.0s than low ratings. Low ratings stood for less than 10 % summed together. The distribution was approximately normal, but unlike a true normal distribution, this one is asymmetric – i.e., it had a tail that extended farther to the left than to the right, such that rating distribution was unbalanced toward positive rates.

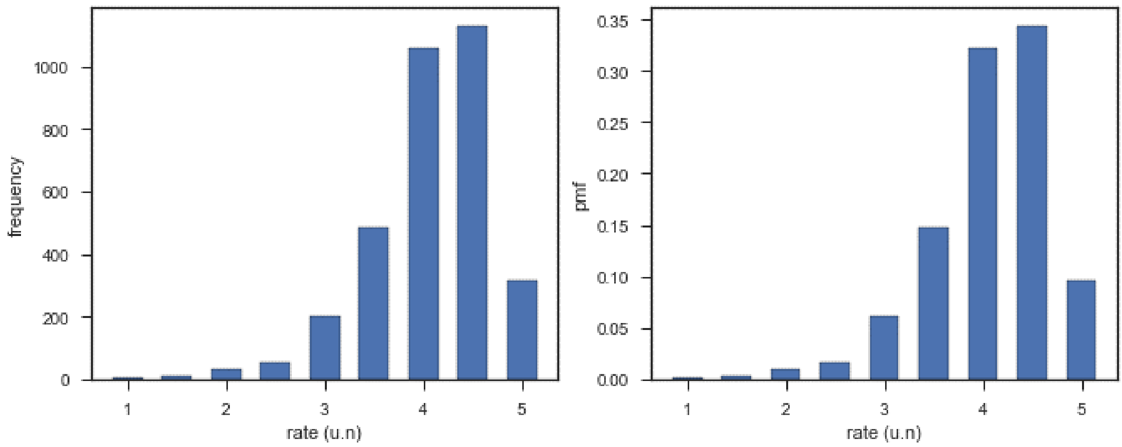

Figure 6 - Rate distribution. Histogram of frequency (left) and probability mass function (right).

c. Price Symbol

Figure 7 shows the price level distribution of the restaurants. This attribute was available in the TripAdvisor webpage as symbols and had the following values:

- **€ - Cheap Eats:** quick-serve or self-service
- **€€-€€€ - Mid-range:** casual, table service
- **€€€€ - Fine Dining:** More formal or dressy

Although such definitions were quite subjective, many users might adopt them as the price they expected to spend in a restaurant. The histogram on the left shows that a total of 2,030 restaurants in the sample, or 66,3%, had been self-categorized as casual or table service restaurants. Only 3.5% per cent of restaurants categorized themselves as fine dining while 30.2% as quick services restaurants.

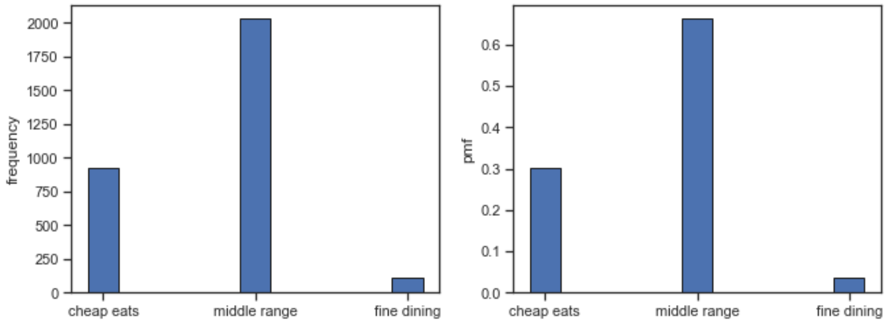

Figure 7 - Price level symbol distribution. Histogram of frequency (left) and probability mass function (right).

d. Price Range

Figure 8 shows the distribution of binned values for the average price range. This attribute was transformed in bins of five because its raw format was in a range - e.g. 5€ - 10€. So, if a price had a value equal to 10, it meant that the expected range of the meal was more than 5 euros and less than 10 euros. A total of 1,308 restaurants or 39%, had put this information on their web pages, resulting in a histogram of only 22 distinct values. The mode of the histogram was 15, with a frequency of 328 restaurants, followed by 20 with a frequency of 274. In other words, a total of 328 restaurants claimed a meal of a minimum of 11€ to at least 15€, in average, and 205 restaurants claimed to have a meal of 21€ to at least up to 25€, in average.

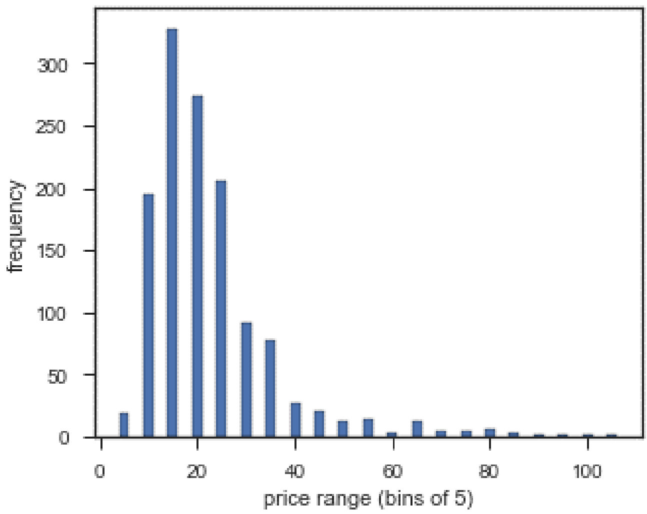

Figure 8 - Binned price range distribution.

The distribution was approximately normal distribution. But unlike a true normal distribution, it was asymmetric and had a tail that extended farther to the right, meaning that the distribution was unbalanced toward lower values.

e. Certificate Awards

According to TripAdvisor, the recipients that had a certificate were described as:

"*… hospitality businesses that deliver consistently great service across the world. This designation is presented to approximately 10% of total businesses on TripAdvisor that have consistently achieved great reviews over the past year. There is no application process for the Certificate of Excellence, and the achievement is earned over time*."

There were some features that an establishment should had to earn such a certificate. Some examples were an overall TripAdvisor rating of at least four out of five, had a minimum number of reviews and had been listed on TripAdvisor for at least twelve months. To be a recipient, TripAdvisor used its algorithms as well as consumer-generated content that considered the quality, quantity, and recency of user reviews as well as the business' tenure on the site.

Figure 9 shows the distribution of the certificate award attribute. The plot below shows the distribution of certificated recipient's. One third of the restaurants, or a total of 2225, being 67.7%, did not have a certificate by excellence, while 1,060 establishments had a certificate, standing for 32.3%. This percentage suggests that many managers were aware of the importance of keeping and adopting a good image online in the TripAdvisor platform.

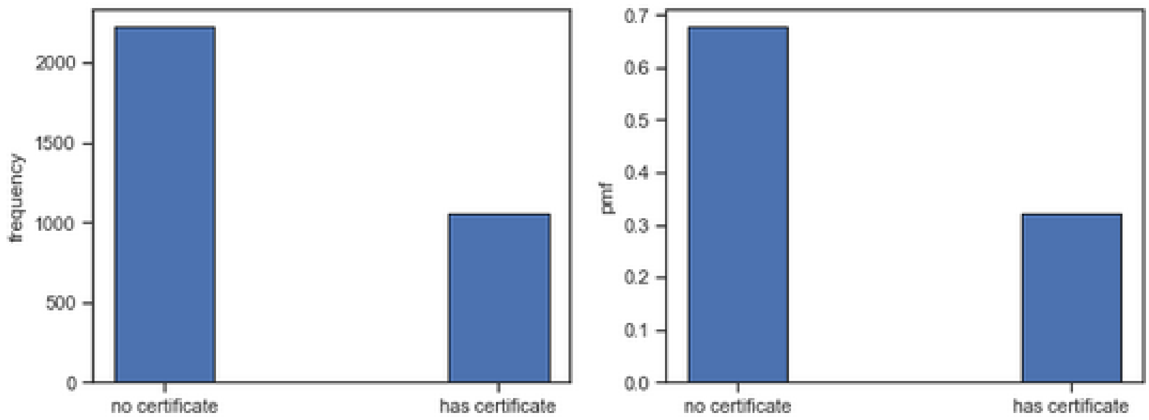

Figure 9 - TripAdvisor certificate of excellence distribution. Histogram of frequency (left) and probability mass function (right).

f. Review quantity

Figure 10 presents the review frequency for the English, the Portuguese, and all languages. The three variables followed roughly the same distribution. English reviews stood for 32% of total reviews while Portuguese reviews stood for 26%. Considering that total reviews were a sum of many different languages such as Spanish, French, or Chinese a percentage of 58% showed the preference of these two languages among TripAdvisor users in Lisbon, especially for the English language, which is not a native one.

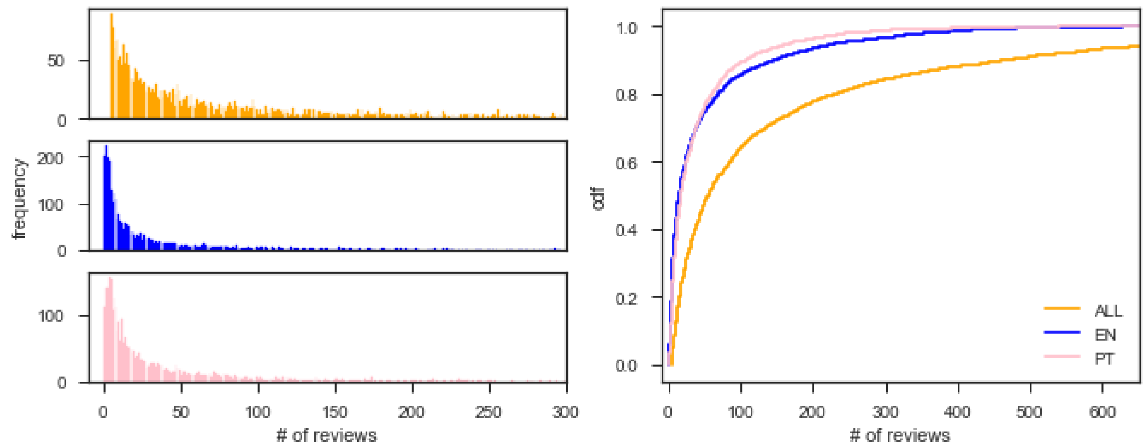

Figure 10 - Total reviews, total English reviews, and total Portuguese reviews distributions. Histograms of frequencies (left) and cumulative distribution function (right).

One interesting characteristic about English and Portuguese review was that, generally, they were available on low to medium reviewed restaurants. The difference was easier to be distinguished in the plot on the right, where the cumulative distribution function showed that 90% of the reviews in English was between the range of 1 to 200 reviews and 90% of Portuguese reviews was in the range of 1 to 100 reviews, while 90% of total reviews was in the range of 0 to 500 reviews.

4.1.4. Relationship between variables

This topic focuses on how restaurant attributes related between themselves. Two variables were related when one variable gave information about the other.

a. Total review and English/Portuguese reviews

As seen in the last topic, the relationship between the total reviews and Portuguese or English reviews seemed to follow roughly the same distribution. Figure 11 plots these relationships.

The upper left plot of the figure helps to verify how total reviews and total of English reviews correlate. It was evident that as the total review grows any reviews in other language accompany this growth, but for English reviews this correlation was the strongest and almost a straight line. The upper right plot shows this relation amongst the 25^{th}, 50^{th} and 75^{th} percentiles. Although for restaurants with high quantity of reviews, or more than 400 reviews, the plots seemed with a lot of "valleys and hill", in the range of 0 to 200 where there were almost 90% of English reviews, the relationship was almost linear.

For the Portuguese reviews, the relationship was also positive, meaning that if a restaurant had a high total reviews value, it was likely to have a high Portuguese reviews value as well, although the relationship was weaker compared to English and total reviews.

The correlation according to the percentile distribution was like the English reviews and total reviews relationship (lower right). The Pearson's correlation as well as Spearman's correlation had both positive and were relatively high for both variables, with magnitudes of 0.947 and 0.936 for English reviews and 0.737 and 0.847 for Portuguese reviews, respectively.

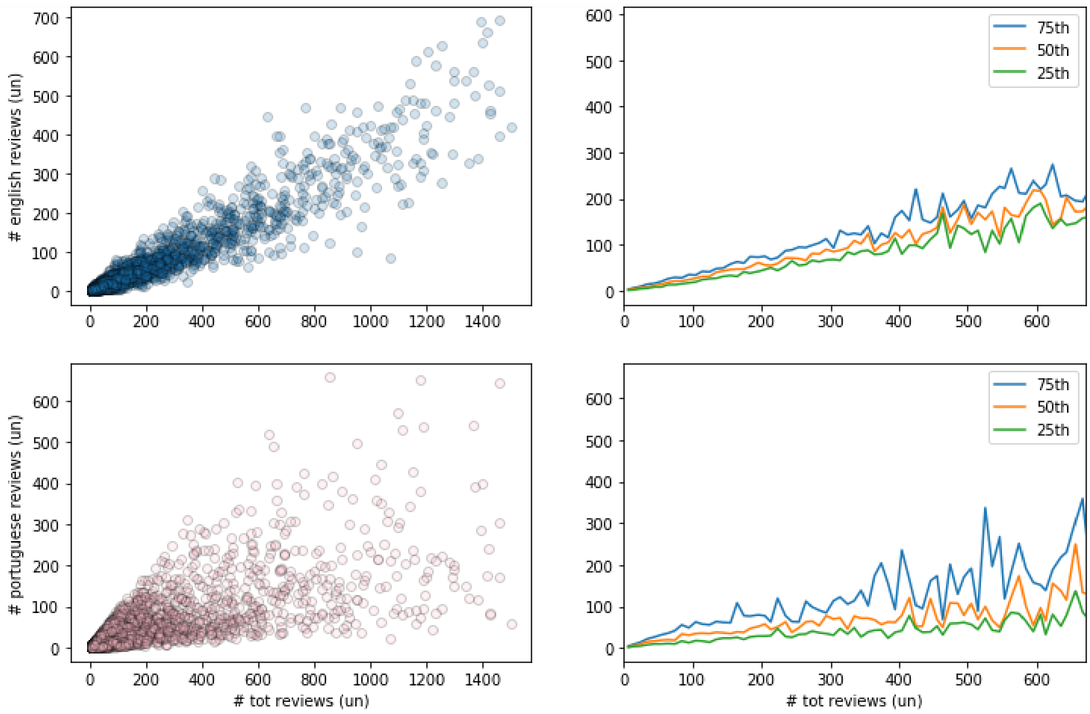

Figure 11 - Scatter plot of English reviews versus total reviews (upper left) and Portuguese reviews versus total reviews (lower left). Percentiles of English reviews for a range of total reviews (upper right) and Portuguese reviews for total reviews (lower right).

b. Aggregate Rate and Price Level

Figure 12 explores the relationship between rate and level price symbol attributes. The plot on the left shows the relationship between the two variables according to their discreet values available in the dataset. The Figure 12 shows the rates and reviews as packed into columns and make clear that fine dining restaurants were not likely to had very lower rates. The plot on the right was the result of adding some random noise to the data for purposes of visualization – a technique called jittering.

The figure in the right shows darker regions due to overlapping data points that were proportional to their density. This version of the plot allows to see two details: one cluster around cheap eat restaurants - *x*-axis equals 1 - and another cluster around rates of 2.5. The second cluster was more distributed across different rates while the first one centred near the same height, with few rates. Although such pattern appeared visually, these variables did not show strong relationship with each other - the Pearson's correlation was 0.04 and the Spearman's 0.002. This resulted because most restaurants had rates of 4s and 4.5s and the variance was too high in these ranges.

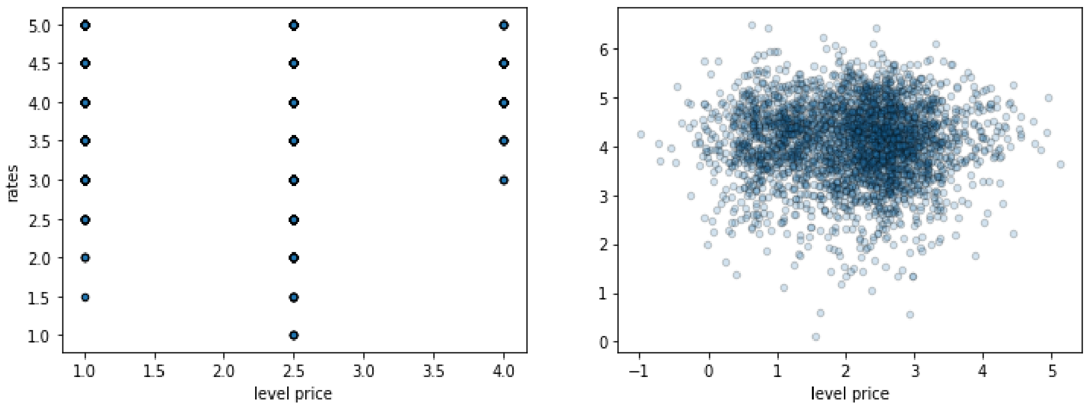

Figure 12 - Scatter plot of rate versus price level symbol for all restaurants non-jittered (left) and jittered and transparent (right).

c. Price Level and Price Range

Another relationship that seems logical is between the price level symbol and the average price range. Since the price level symbol definition was quite subjective to interpret, restaurants that showed a price range should help users to estimate how much they would spend as another source of information. In Figure 13 the left boxplot derives directly from the dataset and the right plot shows the level price jittered by 0.5, to help visualize differences and patterns. The boxplot shows that, as the price level raised, the mean average price also raised. The scatter shows that as the price level raised, the numeric range slightly varied and raised too. Both the Pearson's and Spearman's were positive, and their magnitudes were 0.481 and 0.557, respectively. This relationship would permit to impute values that were missing in case of further analysis of prices.

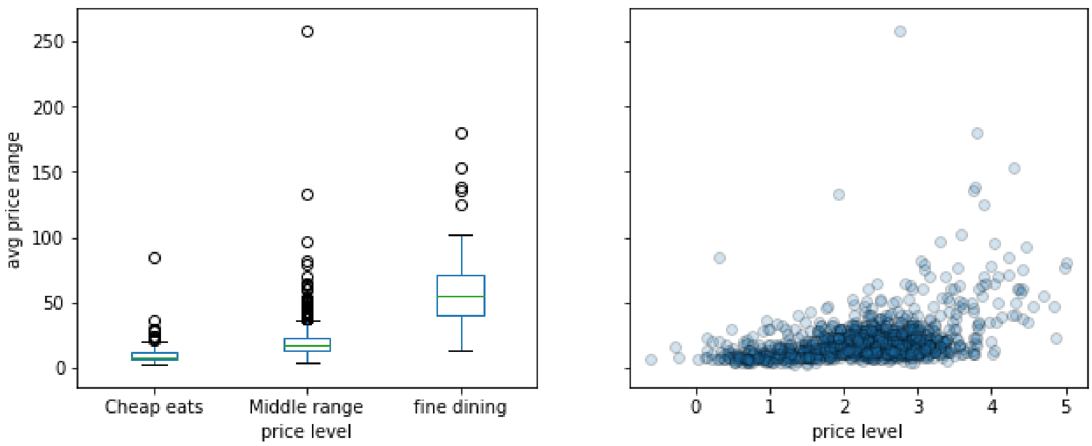

Figure 13 – Boxplot of price level symbol versus price level range for the restaurants in the dataset (left) and jitter scatter plot (right).

d. Pearson's and Spearman's correlations for all numeric variables

The following tables illustrates the correlation values between all numeric variables in the restaurant dataset. Table 5 presents all Pearson's correlations and Table 6 all Spearman's correlation.

Some relationships such as the total reviews and certificate could be explained by the own rule to earn a certificate. As described earlier, TripAdvisor gave a certificate only by a certain quantity of reviews. The price and rate correlation magnitude were near zero, suggesting that other factors were likely to define the overall evaluation of a restaurant rather than the menu's price. For some attributes, like the number of Portuguese reviews and certificate attributes, the Spearman's correlation showed higher magnitudes than Pearson's correlation ($\rho_{Spearman} = 0.530, \rho_{Peason} = 0.392$).

The price level also presented a positive correlation with the price range attribute for Spearman's correlation and for Pearson's correlation ($\rho_{Spearman} = 0.544$; $\rho_{Peason} = 0.481$), being the former higher than the latter. This was explained by the robustness of Spearman's in the presence of outliers and skewed distributions.

Table 5 - Pearson's correlation between numeric restaurant attributes.

	Rate	**TotReviews**	**Certif.**	**Price Level**	**Price range**	**En. Reviews**	**Pt. Reviews**	**Bin. Price**
Rate	1.00							
TotReviews	0.039	1.00						
Certif.	0.236	0.489	1.00					
Price level	-.004	0.205	0.074	1.00				
Price range	-.013	0.186	0.122	0.481	1.00			
En. reviews	0.075	0.947	0.46	0.222	0.186	1.00		
Pt. reviews	-.004	0.737	0.392	0.266	0.240	0.631	1.00	
Bin. Price	-.057	0.215	0.135	0.538	0.994	0.202	0.281	1.00

Another interesting observation was the comparison between the price level and the two different languages as the correlation between price level and Portuguese reviews is stronger than for English. The correlation between price level and Portuguese reviews was stronger than for price level and English reviews.

Table 6 – Spearman's correlation between restaurant attributes.

	Rate	Total Reviews	Certif.	PriceLevel	Price Range	En. Reviews	Pt Reviews	Bin Price
Rate	1.00							
TotReviews	-.057	1.00						
Certif.	0.217	0.628	1.00					
Price level	-.002	0.223	0.067	1.00				
Price range	-.112	0.301	0.167	0.557	1.00			
En. reviews	0.026	0.936	0.602	0.232	0.266	1.00		
Pt. reviews	-.112	0.847	0.530	0.277	0.387	0.700	1.00	
Bin, Price	-.119	0.297	0.159	0.544	0.983	0.254	0.374	1.00

4.2. Review Dataset - Exploratory Data Analysis

This topic follows the same organization of topic 4.1, while exploring a different dataset. It begins with an exploratory data analysis of each review attribute, following the sentiment analysis results and ends with the correlations between variables.

4.2.1. Review Rating

Figure 14 shows the distribution of review grouped by ratings for each language. It can be seen in the figure that most of the reviews had high rates – such as 4s, 4.5s, and 5s - being the remaining rates not very sizeable. For English Reviews, barely 6% of the samples was very low (rated as 1), 4% was rated as low (value of 2) and 8% was rated as 3. For Portuguese reviews, barely 5% of the samples was rated as 1, 4.7% for rates that equalled 2 and 11% for rates of 3s. Once again both languages presented a similar distribution. The mean and standard deviation for both distributions was very alike ($\mu_{en} = 4.21, \sigma_{en} = 1.16$; $\mu_{pt} = 4.09$, $\sigma_{pt} = 1.11$).

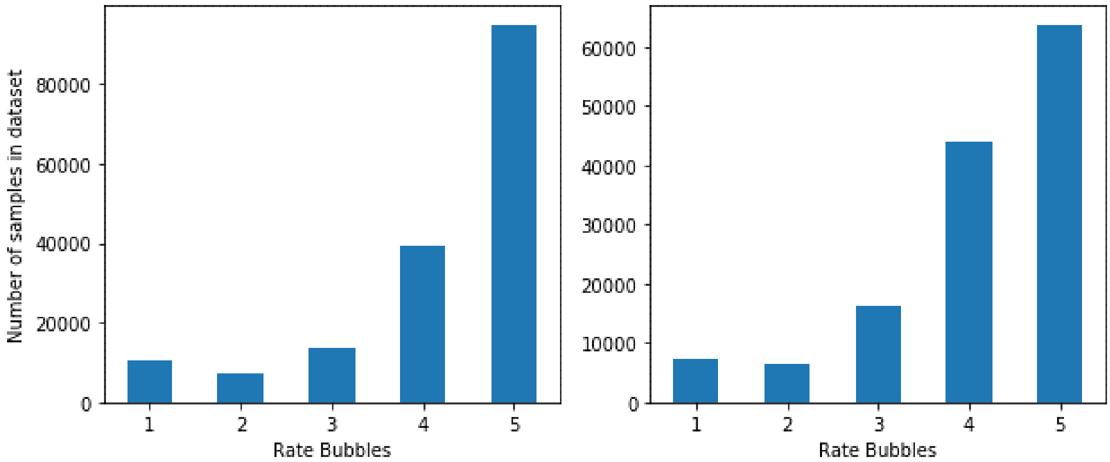

Figure 14 - Review distribution of English (left) and Portuguese (right) languages.

Figure 15 shows the distribution of average number of words grouped by review rate. The figure shows that the average number of words was somewhat related to the rate the users attributed to a review. The number of words, on average, was high for low rates and decreased as the rate increased. Despite such pattern was present, on average, the standard deviation for all rates was high - the mean and standard deviation for English distribution was $\mu_{en} = 80.89$ and $\sigma_{en} = 66.88$, for the Portuguese distribution was $\mu_{pt} = 56.56$ and $\sigma_{pt} = 50.32$. This means that this apparent effect had many exceptions such that some low rated reviews had very low length and vice-versa.

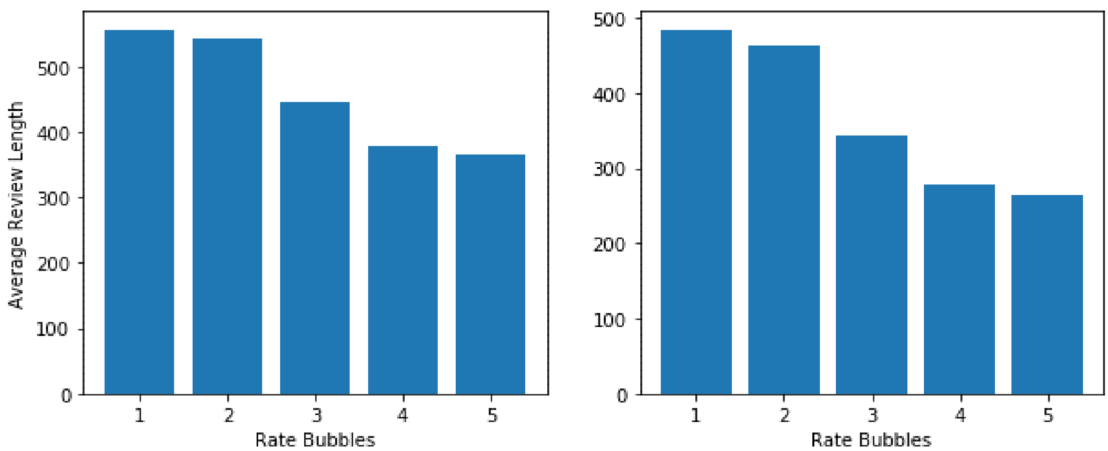

Figure 15 - Count of words per reviews of English (left) and Portuguese (right) languages.

4.2.2. Reviewers Location

Table 7 lists the top five reviewer's location (countries). All locations were formatted with a Python's package called Geopy.

The top three locations stood for 44.36% of the English reviews, while for the Portuguese reviews the distribution was slightly different - the top two countries stood for 70.8%. Interestingly for the English reviews, while for Portuguese reviews the distribution was slightly different – the top two countries stood for 70.8%.

Interestingly for the English Reviews, although the first two locations were clearly countries that had English as their native language, the third was Portugal, a non-English native language country. Another aspect of Portuguese reviews was that other non-Portuguese countries gave Portuguese reviews such as Spain and United Kingdom. For English reviewers, a total of 41,909 reviewers did not show this information on their profile, or 19.6%. For Portuguese reviewers, 42,461 profiles did not disclose the location information in the profile, resulting in 24.6%, a higher ratio than English reviews.

Table 7 - Top five reviewer's location available in the dataset.

Rank	English Reviews' Location	N	Portuguese Reviews' Location	N
1st	United Kingdom	43,307	Portugal	83,549
2nd	USA	29,260	Brazil	38,568
3rd	Portugal	21,965	Spain	1,474
4th	Canada	7,606	United Kingdom	959
5th	Australia	5,002	USA	762

4.2.3. Reviewers Contributions

Figure 16 plots the distributions of English and Portuguese reviewer's contribution. Both attributes had a similar distribution. The contribution counted for any TripAdvisor available possibilities – e.g. restaurant, hotel, or attraction. On average, those who reviewed a Lisbon restaurant in English had reviewed 83 times any TripAdvisor page, but this value was misleading in the sense that the mode is 1, is 1, followed by two with 16,104 and 10,613 users in total, respectively. For Portuguese reviewers, in average, 86 reviewers had previously reviewed some TripAdvisor page, but as well as English reviewers, the majority consisted of 1 or 2 contributions with 15,905 and 8,237, reviewers, respectively. An astonishing value of 270 Portuguese profiles that had contributed at least 4,000 times and 15 English profiles that had contributed at least 9,000 were found. Besides these outliers, the pattern was the following.

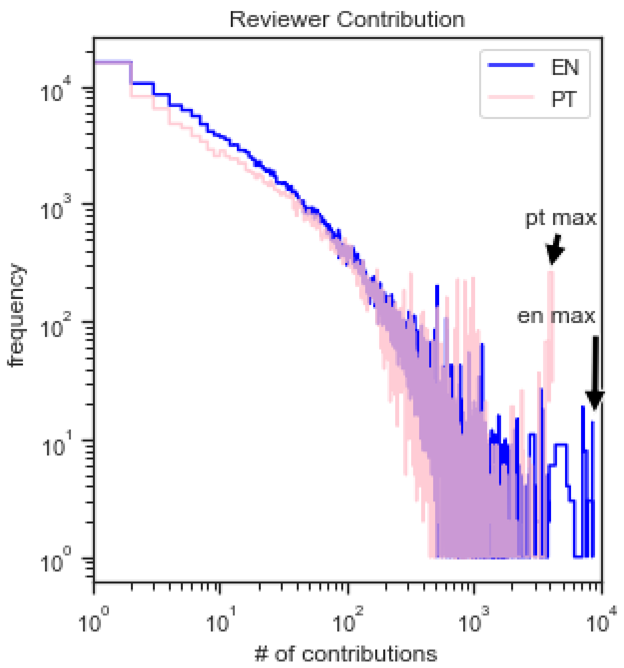

Figure 16 - English and Portuguese reviewer contribution distribution.

As the number of contributions increased, the frequency abruptly decreased. After 200 contributions the values became erratic, having one to ten contributions. But as a standard, many reviewers contributed just once.

Figure 17 plots the number of co-occurring reviewers – the number of reviewers in the dataset that had already reviewed a Lisbon restaurant once. There were 123,502 different English reviewers and just 64 distinct values of previously contribution to a restaurant. For Portuguese reviewers, there were 70,940 reviewers and just 116 different values. The maximum value met in the dataset was 176 for English reviewers - meaning that someone had reviewed this number of Lisbon restaurants. The mode was 1 with a frequency of 84,063. The frequency decayed abruptly as the number of previously contribution raised. For Portuguese reviewers, the maximum contribution was 342 reviews. The mode was also 1 with a frequency of 45,413. The value also decayed abruptly and stabilized in 1. The almost straight line with negative slope evidenced that the distribution decreased exponentially as the number of contributions to restaurant in Lisbon increased. The values became erratic after 40 contributions, having zero up to five contributors after that. A total of 235 contributors could not be named and were tagged as ‘A TripAdvisor reviewer on Facebook’.

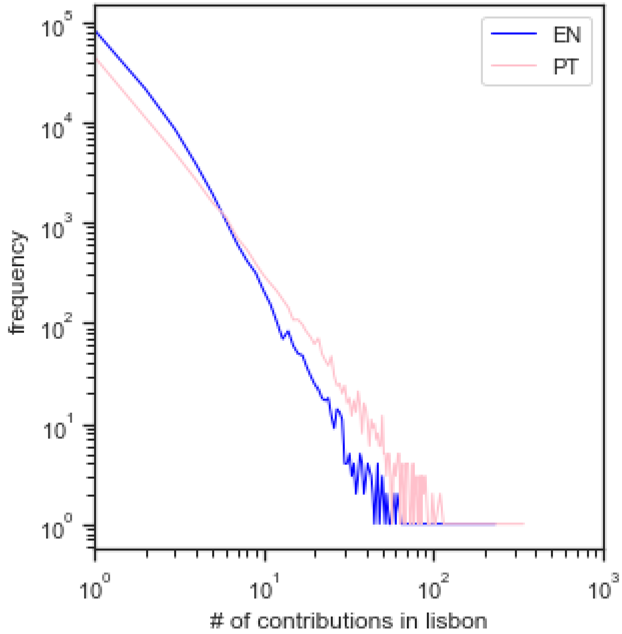

Figure 17 - English and Portuguese Lisbon re-incidents contributors.

4.2.4. Sentiment Orientations Scores

Figure 18 plots the sentiment variation scores for Portuguese, English and both languages together in a time series. It can be seen from the figure that in the beginning – starting in 2007 - the sentiment evaluations for all three distributions were sparser, and then became less wide as the time advanced (especially for positive scores). This happened because in the beginning the total number of reviews were smaller compared to other periods, so the month average scores were more vulnerable to outliers.

When joining the two languages together, this effect became less apparent and the gap between positive and negative reviews was more perceptible.

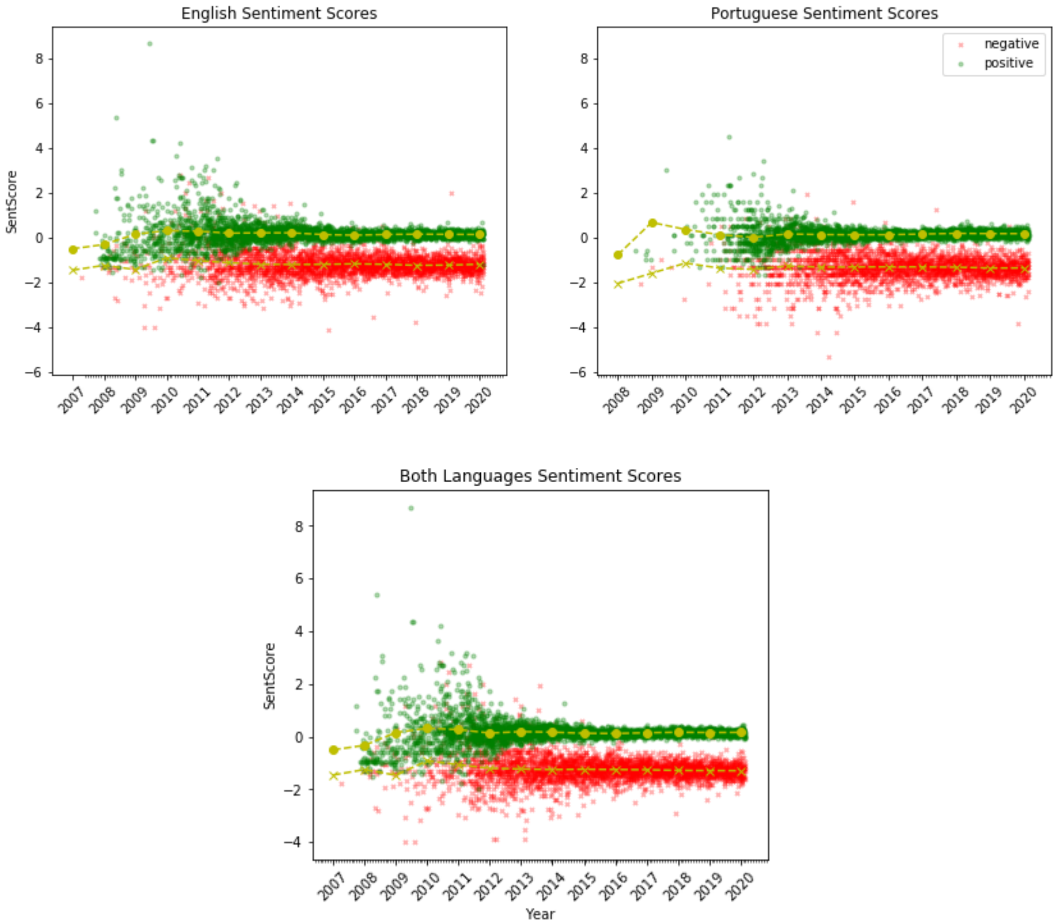

Figure 18 – Sentiment Polarization scores varying throughout the years for English (upper left), Portuguese (upper right) and overall (lower middle) reviews.

At the end of both languages plot, the negative reviews became more negative and the gap increased. The yellow dashed lines in the plots represents the mean score by year and highlights these behaviours. The apparent effect was that the positive rates were centred around zero and below it. This happened because the lexicon scores were standardized - meaning that they were centred around the mean, being the overall mean positive.

Figure 19 plots the distribution of the lexicon scores grouped by rating. Curiously, even when restaurants had lower rates - e.g., 1s, 1.5s, or 2s - the lexicon orientation mean was above zero. As the rate increased, the lexicon scores range widened, but the mean values per group did not varied much from the overall distribution, showing that restaurants with high ratings had a wider score ranges.

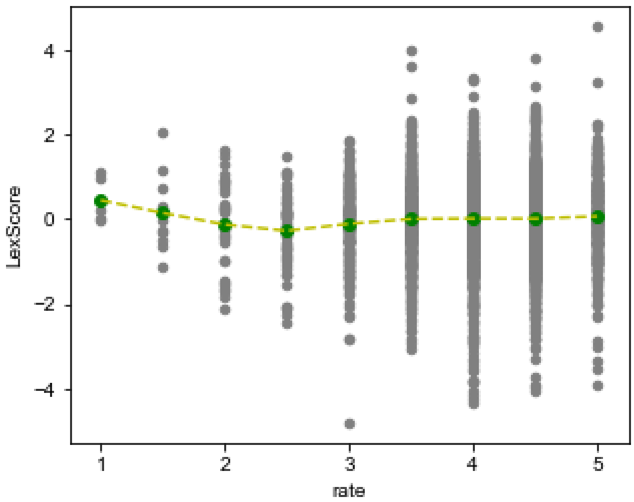

Figure 19 - Sentiment Score variation per Restaurant overall rate. Gray points are the proper averaged sentiment score, the green points the average score per rate, and the yellow dashed line links the mean.

Figure 20 shows the result of the sentiment orientation in a time series for a sample of five distinct restaurants. This image illustrates the arrays of sentiment score per restaurant that resulted from the analysis described on topic 3.2.

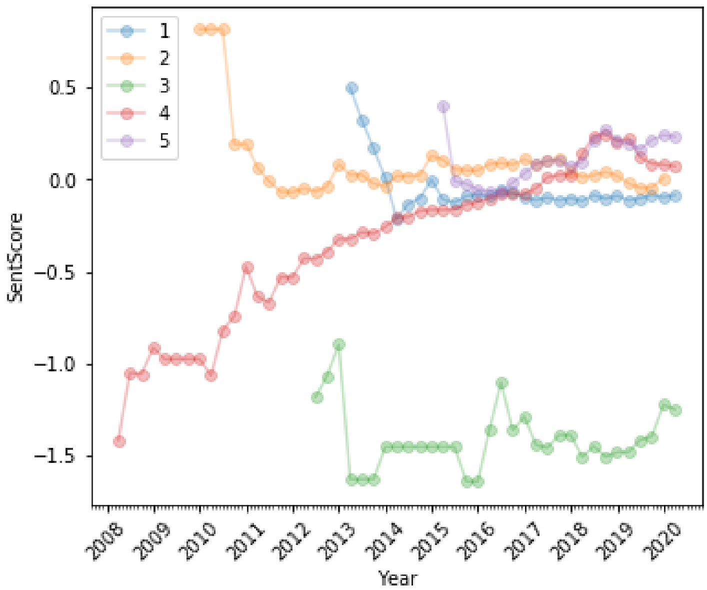

Figure 20 – Quarters' Lexicon Scores variation over time, each point is an EWMA.

These arrays were used to create the adjacency matrix for the network of restaurants. In the plot each point referred to an exponential weighted rolling average with span 4 – in other words, it represented the sentiment orientation per quarter. The figure shows that the restaurant with id 4 was the earlier restaurant in operation to date. This restaurant revealed a positive sentiment evolution score over time. The restaurant with id 3, on the other hand, did not perform well - though at the end a sentiment score subtly increased. Another detail observed was that the restaurant with id 3 did not have reviews throughout all the time window, lest staring from 2012.

When calculating the same variation in time, the intersection of values between restaurants were taken into consideration to overcome this limitation – if restaurants 3 and 4 were compared, only values after 2012 were considered.

4.2.5. Text Statistics and Model Metrics

Table 8 shows the descriptive summary for English and Portuguese languages that was commonly presented in text analysis, illustrating the differences between these two languages. One interesting information derived from the Table 8 was that English reviews have more words than Portuguese reviews, but its vocabulary size was lower compared to it. These values suggest that the semantic space for Portuguese was higher than for English language, as reflected by the last column Lexical Diversity. On average, each word from the English vocabulary occurred 139 times, and from Portuguese vocabulary, 79 times.

Table 8 - Summary Statistics for Each Language in Corpus

	Documents	**Sentences**	**Words**	**Vocabulary**	**spd**	**L.D**
English	165,454	822,386	13,627,804	98,109	4.97	139.08
Portuguese	137,723	491,657	7,972,557	100,045	3.56	79.68

* spd: sentences per document, L.D: Lexical Diversity

To verify the performance of the lexicon-based Sentiment Analysis, different classification metrics were examined. The metrics were examined with an implicit assumption that if a review had a positive rate, it leaned to had a positive sentiment – in other words, the model considered that a positive rate had positive sentiment embedded and vice-versa. Table 9 presents the Accuracy, Precision, Recall and F1-Score metrics. Considering that this was a simplistic approach, it is reasonable to say that the resulted very well and at the same time was capable to capture the sentiment for the overall reviews.

Table 9 – Baseline Scores comparing to Dataset Reviews Rate

Lexicon Dictionary	Accuracy	Precision	Recall	F1-Score
AFINN	0.93	0.91	0.93	0.92
SentiLex-PT-02	0.87	0.91	0.87	0.88

Regrettably, such approach had clears drawbacks. Two of the most apparent struggles were ironies and negations, in which was very hard to capture only counting word lexicons and computing its sum. Consider the following excerpt, classified as a negative orientation, but that was clearly positive:

"My. God. Please eat here. You're really a horrible person with no taste if you don't. Justin *is an artist who has created a flavor explosion with every dish."*

The AFINN lexicon scores "God" with +1, "horrible" with -3, "no" with -1 and "please" with +1, so the resulting verdict was negative. Although the resulting score being negative, the reviewer was clearly using irony in its statement. Moreover, another bias resulting from this approach was that summing lexicon scores tended to favour lengthier reviews. Even though, the approach resulted good scores for both datasets. To see more reviews in English and Portuguese and how the model evaluated them, please refer to appendix C.

4.2.6. Review Attributes Correlations

Tables 10, 11 and 12 list the correlation values for all the numeric attributes in this dataset attributes. Besides the Review Helpful and Reviewer Contribution to the website attributes, other variables did not show strong correlation. As pointed earlier, it was possible to see from the Spearman's correlation that the length of the reviews and the sentiment score were positively correlated. The correlation holds for either Portuguese or

English – consequently for the two languages together. Also, the number of contributions was also highly correlated with the helpful of the reviews.

Table 10 – Correlation between English Review's attributes

English	Review Rate	Review Helpful	Reviewer Contribution	Number of Words	Lexicon Scores
Review Rate	1.00				
Review Helpful	-.163	1.00			
Reviewer Contribution	-.167	0.924	1.00		
Number of Words	-.145	0.196	0.247	1.00	
Lexicon Scores	0.418	0.036	0.046	.324	1.00

Table 11 - Correlation between Portuguese Review's attributes

Portuguese	Review Rate	Review Helpful	Reviewer Contribution	Number of Words	Lexicon Scores
Review Rate	1.00				
Review Helpful	-.188	1.00			
Reviewer Contribution	-.192	0.912	1.00		
Number of Words	-.206	0.148	0.196	1.00	
Lexicon Scores	0.341	0.031	0.022	.105	1.00

In a nutshell, these correlations showed that as more words a review had, it was likely to be of some frequent contributor ($\rho_{Spearman} = 0.218$) and likely to had low rates ($\rho_{Spearman} = -.143$). The number of words correlated positively with the lexical score ($\rho_{Spearman} = 0.201$). As evidencing the assumption about positive rates and lexical score, the correlation between these two variables was positive ($\rho_{Spearman} = 0.375$).

Table 12 - Correlation between for both languages Review's attributes

Both Languages	**Review Rate**	**Review Helpful**	**Reviewer Contribution**	**Number of Words**	**Lexicon Scores**
Review Rate	1.00				
Review Helpful	-.175	1.00			
Reviewer Contribution	-.176	0.921	1.00		
Number of Words	-.143	0.164	0.218	1.00	
Lexicon Scores	0.375	0.034	0.035	.201	1.00

Figure 21 shows the lexicon orientation per rates for all the three distribution. It can be seen from the figure that as the number for rate per review increased, the lexicon scores also increased. This pattern was present in the three distributions for the three distributions.

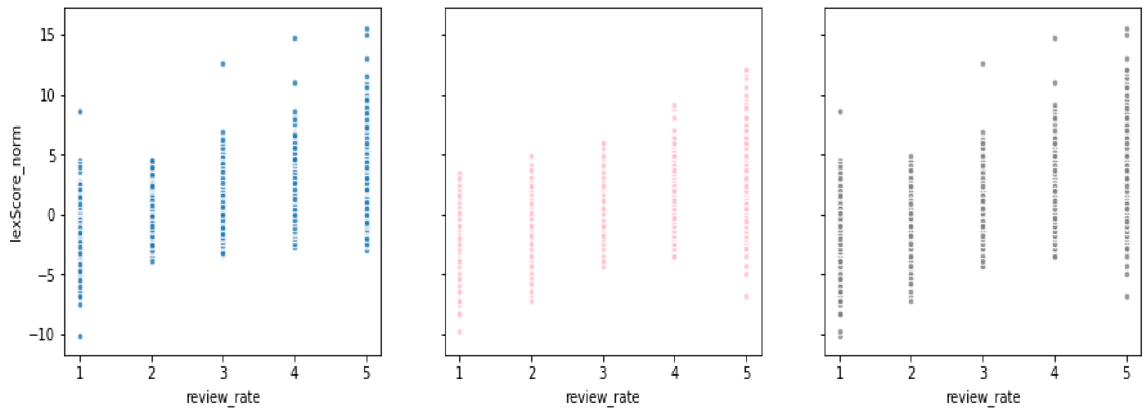

Figure 21 – Reviews' lexicon score per rate for English (left), Portuguese (middle) and both together (grey).

4.3. Network Analysis Results

This topic explains the resultant network and presents the network statistics and properties. It ends by exploring the hypothesis test results.

4.3.1. Network Statistics

The final network had a total of 2,383 nodes, meaning that 73% of the restaurants had a statistically significant link. The graph density was 0.00139, or 1.39%, meaning that the nodes did not connect many times with each other. The average degree of the networks is 3.29, so on average, each degree had three links. Figure 22 plots the resultant network. The size of the nodes was proportional to the popularity of a restaurant mod 15. The width of the links was proportional to sentimental variations co-occurrences and its colour was proportional to the t-test value – darker blue means stronger links and lighter blue means weak links. As it can be seen from the figure, the visual effect was a messy distribution of nodes, if no pattern spotted - as if the nodes were almost at random.

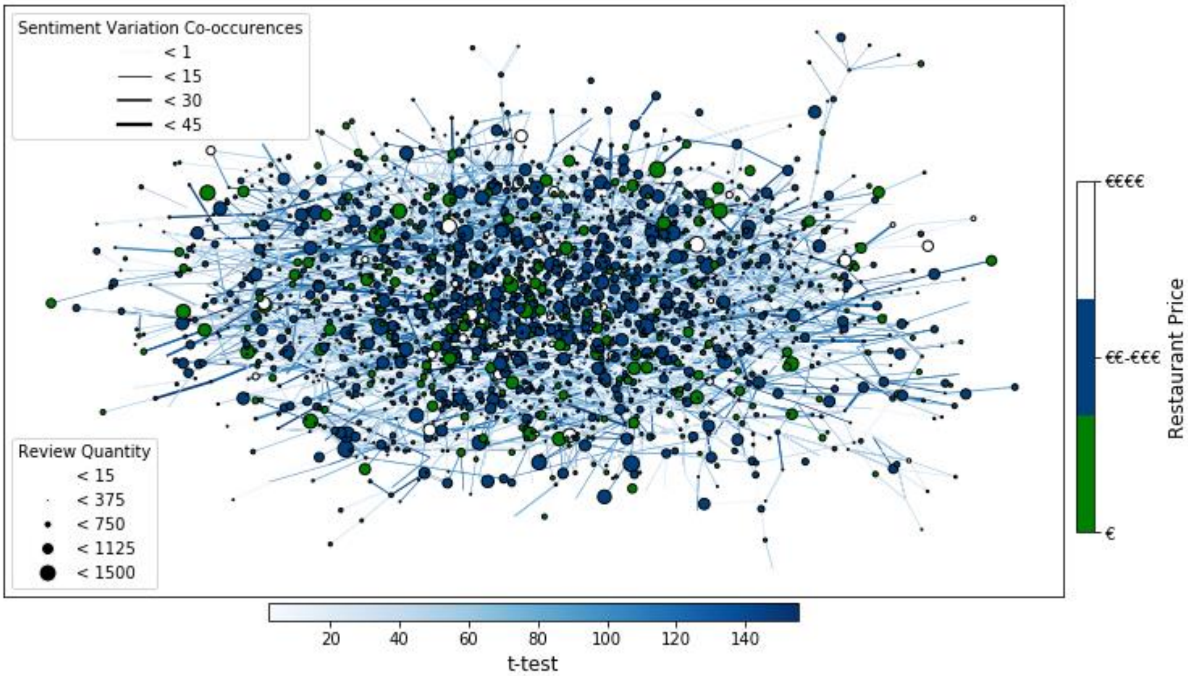

Figure 22 – Network of co-occurent sentiment variation in time. The nodes are the restauants and the links the number of similar variation of sentiment in time.

This can was emphasized by the transitivity of the network, if a value of 0.004 or 4% – the fraction of all possible triangles that existed in the graph - meaning that only 4 out of 100 nodes formed triangles in the network. Trying to form communities leaded to 65 different ones with each community with 52 nodes, on average. For each of the communities it was possible to compare if the average per community were similar for each property by computing the standard deviation of the means. Table 18 lists the values for the rate, popularity (number of reviews) and price variables. As can be seen from the table the standard deviation was small, evidencing that the attributes were not discriminated very well within the communities.

Table 13 – Mean and Standard Deviation for rate, popularity, and price community distribution.

Attribute	Mean	Std
Rate	0.773	0.041
Popularity	0.127	0.055
Price	0.782	0.116

4.3.2. Network Properties

The Lisbon network was composed of undirected links. Besides, the metrics was based on an intrinsic similarity measure that was computed by takin into consideration the sentiment variations in time. The following illustrates two important distributions of the network, the node degrees, and the path lengths.

Figure 23 plots the network node degree distribution in a log-log scale. The almost straight line from the figure evidenced that the node degrees followed an exponential distribution. The mode was 1, meaning that many restaurants connect only once to another restaurant. As the number of nodes increased, the node degree decreased exponentially.

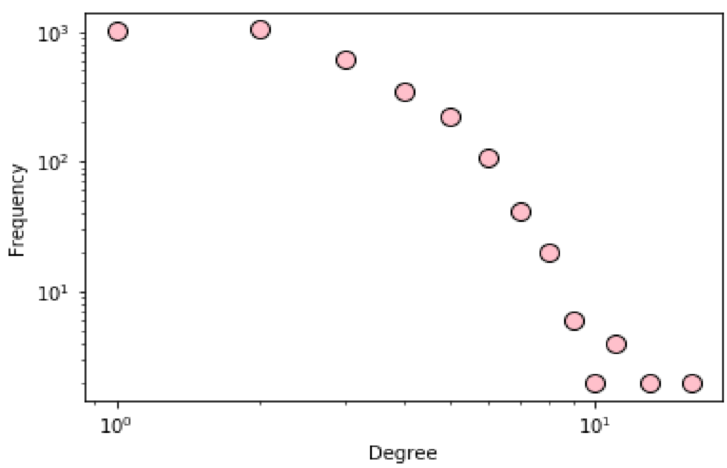

Figure 23 – Nodes Degree Distribution

Figure 24 plots the path lengths distribution, showing a normal distribution clearly. The average path length of the graph is 9.82, or 10 links per node on average with a standard deviation of 2.73 or 3 links per node. It can be seen from the figure that the resultant network had a considerable number of links.

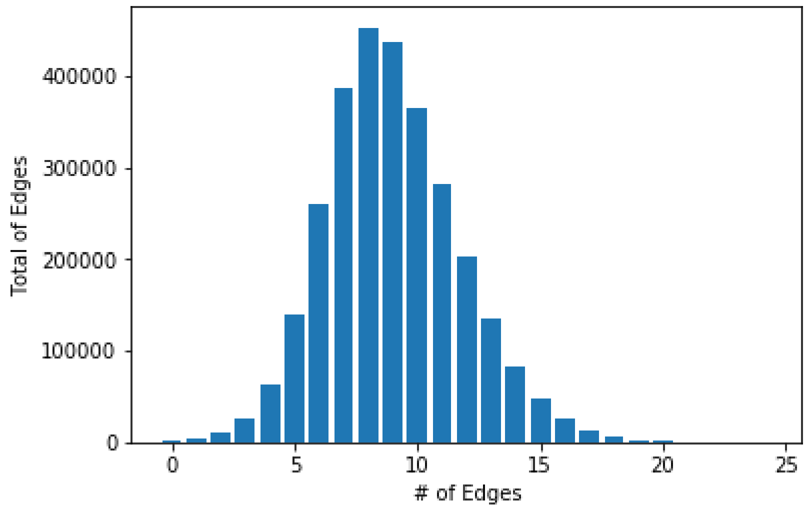

Figure 24 – Edges Distribution

4.3.3. Testing the Network Hypotheses

To verify whether the price, the rating, and the cuisine type proxied to sentiment variations, the nodes were grouped according to their edge distances and were compared to a randomly generated network. For each focal node i, groups of ties to each link distance j (in the range 1 to 10) arranged the data such that the values of common shared attributes, divided by the number of links for each node i, were computed. This calculation aimed to see whether the link distance j follows a distribution differently from the random network. The sentiment co-variation network links and nodes per distance j was defined as an array called A. The same array for the random network was called B. So, the operation between the arrays A and B was expected to show a delta value, Δ, decreasing as the number of links increase.

$$\Delta = \frac{(\boldsymbol{A} - \boldsymbol{B})}{\boldsymbol{B}} \tag{3}$$

Figure 25 plots the distribution for the price variable. It was possible to see that the actual value of similar ties per link distance did not vary too much from an arbitrary distribution as the *y*-axis was near 0 and the maximum difference between the actual and generated network was 0.05 negative. This evidenced that the price distribution in the network was almost arbitrary, and that the link distance neither increased nor decreased as a function of the price. Since there was no correlation between neighbours' similarities and the price attribute, it was not possible to refute the $H_{0\text{-}A}$

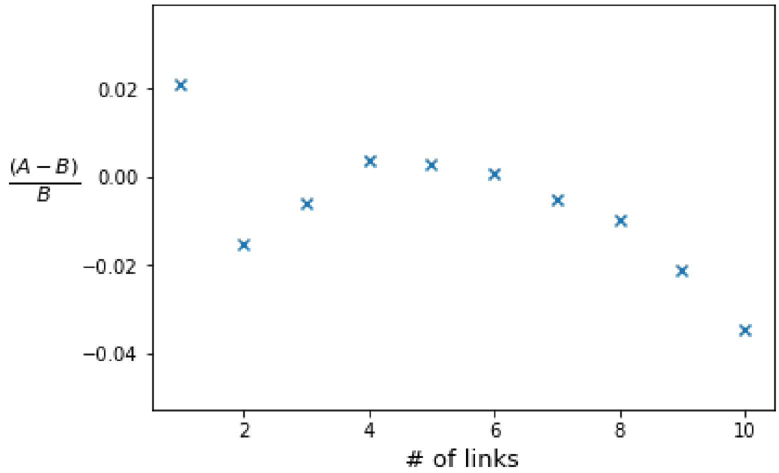

Figure 25 – Difference of the mean value over the difference between the actual distribution and random distribution for the price variable.

Figure 26 plots the same procedure but for the rate variable. Again, the plot showed that the difference between the actual and generated network did not vary too much from a random distribution as the y-axis values were near 0 for all the link distances ranges. Therefore, for the rate attribute of restaurants, $H_{0\text{-}B}$ could not be rejected as well.

Figure 27 plots the distribution value for the cuisine type attribute. A slightly difference from the previous two calculation was that the similarity of ties was calculated using Jaccard Distance - the values of such attributes were categorical strings - and averaged by the total number of links j for a node i. Again, it was possible to see that the variation from a random distribution rather than arbitrarily. Therefore, for the cuisine type attribute, $H_{0\text{-}C}$ could not be rejected as well.

None of the restaurant attributes used as metrics showed an increasing or decreasing pattern proportional to the proximity of the restaurants. In fact, no pattern was showed at all. This suggests that other factors might capture the spill-over sentiment for restaurants rather than the fixed characteristics of the restaurants. Other possibility is that such spill-over was not presented for the available data.

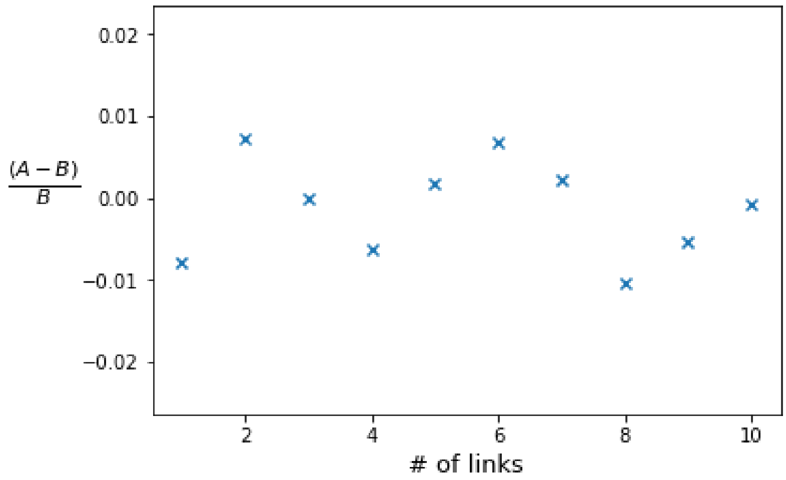

Figure 26 - Difference of the mean value over the difference between the actual distribution and random distribution for the rate variable.

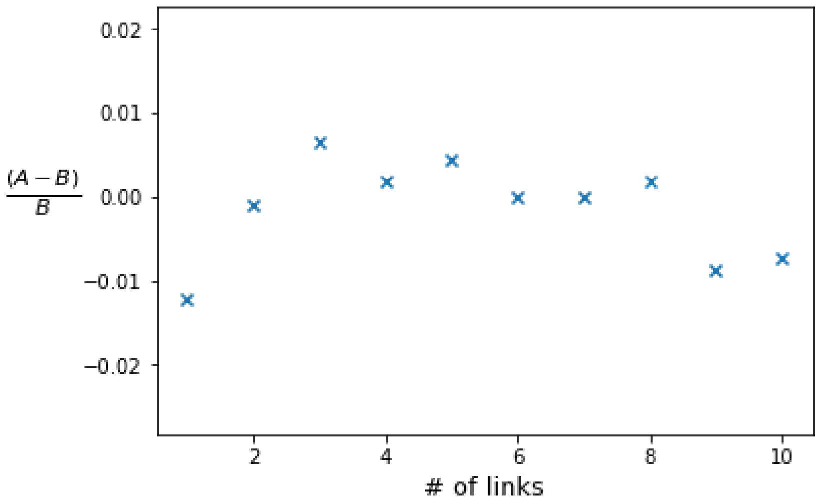

Figure 27 - Difference of the mean value over the difference between the actual distribution and random distribution for the cuisine type variable.

5. Discussion

The number of restaurants in Lisbon is unusually high, as well as the distribution of establishments throughout the city. It is reasonable to say that the distribution of establishments all around the city is the result of a tourism gentrification that occurred in Lisbon since 1990s and 2000s (Barata-Salgueiro et al., 2017) and persisted as one of the strategies of Lisbon to struggle against the 2008-2007 crisis (Sequera, Nofre, 2019). The distribution of first reviews by year evidence this cultural process as the restaurants had a peak of first reviews around 2014 - similar of what occurred in hotel industry (Richard, Marques, 2019). After the rapidly online popularity increase from 2007 to 2014, the number of reviews then started to decrease. Possible explanations would range from people deciding to eat out less than before to people reducing the reviewing habit. Although most restaurants in Lisbon still are of traditional European types such as Portuguese, Mediterranean, and Italian, other kind of cultural ethnics are also encountered. Such presence of distinct cultural cuisines, specially of Asian and Indian types, supports the Lisbon's integration in the international economy as examined by Fonseca & Malheiros (2012). Besides, some restaurant attributes make Lisbon very attractive for the eatery consumers, namely, the average price and the overall good rates. The overall good rating encountered in this study are in line with the distributions found in studies about eWOM that also evidenced a majority of positive values (Taboada et al, 2011; Chaves et al., 2014, Chevalier & Mayzlin, 2006; Pantelidis, 2010; Zanibellato, Rosin & Casarin, 2018). An interesting correlation found for Lisbon restaurant is between total reviews and price range, meaning that a restaurant that is popular is likely to have a higher price range. Such correlation was also found in Korean restaurants (Yim, Lee, & Kim, 2014).

Considering the reviews, the results showed a bias for high rates, showing an unbalancing towards positive values. This phenomenon is also observed in other hospitality services related and non-related studies (Chevalier & Mayzlin, 2006; Pantelidis, 2010; Zanibellato, Rosin & Casarin, 2018), evidencing that online reviewers are likely to express their opinions when they have a good or positive experience. Furthermore, the skewness of rate's distribution is consistent with earlier related studies with restaurants (Jurafsky, Chahuneau, Routledge & Smith, 2014) and movies reviews (Potts, 2011).

Non-trivial computations and metrics tested over the reviews' sentiment variations and showed how it related to the review rate. First, by computing sentiment scores, the lexicon-based approach captured well the overall sentiment orientation of the reviews as a document level, which in fact was supported to be effective to review or products evaluations (Liu, 2016). The resulting lexicon score showed positive bias as well (Taboada et al., 2011). Notwithstanding, aggregating the sentiments scores by an overall restaurant value did not correspond well, and consequently the resultant scores were not used in further analysis. The cause suspected of this discrepancy with the overall restaurant rates was likely because other metrics might influence the aggregate rate calculation on the website that were not retrieved in this study, such as separate rates for ambiance, service, and food**.** Another important finding was that lexicon-based approach was susceptible to linguistic features such as metaphors and ironies (Liu, 2015). To capture such intricacies, other methods should be applied (Socher et al, 2013) being the payoff the complexity of the implementation.

The assumption made that sentiments could be explained and proxied to restaurant' characteristics was not supported, since the variations of sentiments for the selected attributes were similar to a random distribution. As appears to be, the service, food, ambiance, and context on restaurants' sentiment evaluations could play an effective and determining bias rather than fixed characteristics of restaurants, such as rate, type of cuisine or price, as was supported by some studies (Gan et al., 2017; Hosany & Gilbert, 2009; Prahalad & Ramaswamy, 2003). As sentiment is a subject feeling and contradictory even among humans, context should be emphasized in future studies as a factor to translate restaurant characteristics. This might have a power in defining customer's values and create meaning (Hosany & Gilbert, 2009; Prahalad & Ramaswamy, 2003; Zaltman, Olson, and Forr, 2015). Although the spill-over was not captured with the approach used, this does not mean that such spill-over does not exist, rather, it means only that it is likely to occur via other dimensions and factors.

Finally, it is important to remark that the approach used here is an interesting methodology in exploring sentiment evaluations and can be replicated to other topics or domains. The sentiment variation in time with a network analysis is also noteworthy because assumes similarities that are implicit to entities.

6. Conclusion

This study approached two different kinds of analysis. First, the exploratory part presented, described, and plotted information related restaurants in Lisbon and their eWOM. Second, an attempt to map restaurants characteristics to sentiments, while examining whether these characteristics were responsible to mould sentiment orientations, was done using different data analysis techniques that captured information in context. The evidence revealed by the data showed that, for Lisbon restaurants' virtual environment, common restaurants characteristics did not proxy to sentiment spill-over as proposed by the study hypotheses. Although the results could not capture sentiment spill-over for any of the metrics cited, future follow-up studies can fine-grain sentiment analysis to better investigate whether entities and aspects proxy to sentiment.

The data examined previously showed an overall positive evaluation for restaurants in Lisbon (not only in rates but also translated into sentiment scores). Besides, no regions of the city concentrated a specific sentiment orientation, rather, the positive bias was encountered throughout the town. Concerning the analysis approach, this research showed how map the variation of sentiments in time. Such observations derive both theoretical and practical implications. Marketers that are aware of the value of eWOM for cuisine industry can get insights from the dissertation results and take advantage of Lisbon showing an excellent evaluation for restaurant by the customers perspective. Also, they can explore the fact of no cluster' regions for specific establishment types, prices, rates, or popularity, and not concern themselves about the location of a future establishment or an expansion, neither whether other establishments can affect their own. Another important insight is that managers can use TripAdvisor and its reviews to make reports about consume sentiment evolutions on the Internet or how they varied in a timely way for their own establishments, identifying important factors that explain such variations.

Some limitations are worth to note. First, since the analysis focused only on one city and industry, the results are difficult to generalize. Particularly concerning the Sentiment Analysis, the simplistic document-level lexicon-based approach struggled to correctly classify negative reviews and considered some positive reviews as negative as well, though the overall scores were good for this field. Concerning the sample, only reviews from TripAdvisor were considered, but other resources could be used as well (e.g. Zomato, Yelp) to evaluate a complete picture of the population and understand whether the results are similar to those reported here. Retrieving other idioms can broaden the results too. Finally, since the study focused just on web source content, the influence of other types of media may not be disclosed (e.g. promotional emails, newspaper, magazines). Incorporating this kind of information in following studies may provide a comprehensive understanding.

Further work can be extended from the results and data used in this research. For example, it is possible to analyse the sentiments in a more fine-grained way and focus on mapping what entities and targets that make Lisbon a very positively rated city and after that, use networks to cluster similar restaurants by these different entities and mapped aspects. Other interesting follow-up suggestion is to develop a system that recommends the restaurants, such that implementing an API that matches a user query by words or other features or do a segmentation analysis using the reviews dataset.

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APPENDIX A

This appendix explains the detailed transformation process to calculate the matrix for the network of restaurants in Lisbon city. First, it is important to emphasize that this is a similarity-based network. Similarity-based network means that the relationship from one restaurant to another is not a crisp structure such as of a family bound (e.g., father of, mother of, sister of, etc) neither and ordered one like the food chain (e.g., producer, primary consumer, second consumer, decomposer). The relationship that bounds one restaurant to another is based on the similarities of sentiment variation in time. The following table is a partial output of the Sentiment Analysis aggregation process referred in topic 3.2. It is a data frame constructed by a node id (the restaurant id) and a vector or sentiments that represent the EWMA score for each quarter:

Table 14 – Sentiment Variation over time for five restaurants

nodeId	2007-06-30	...	2019-03-31	2019-06-30	2019-09-30	2019-12-31
1	NaN	...	0.095124	0.082182	0.076480	0.069993
5	NaN	...	0.054468	0.053570	0.038532	0.028884
8	NaN	...	0.343621	0.368433	0.371066	0.370058
11	NaN	...	0.152986	0.126690	0.132147	0.088955
15	NaN	...	NaN	0.059844	0.247302	0.458896

* NaN: periods that a restaurant has not been reviewed yet.

The first step needed was to verify the sentiment variation from quarter to quarter. This calculation is what gives the variation per quarter and the signal – if was positive or not. This is obtained by subtracting the columns using a function called diff. If the result is negative, it means that the sentiment per quarter decreased and is negative, it is considered positive otherwise. Table 15 illustrates the subtracting operation. Two restaurants are considered to have the same variation in the quarter period if they signal are the same. To compute the number of similar sentiment variations, the X-NOR logic operation was used as assistant. The X-NOR is commonly known as Exclusive NOR in the computer science. Table 17 represent the results between two but that go to a XNOR operation.

Table 15 – Difference over quarters sentiment variation

nodeId	2007-09-30 2007-06-30	...	2019-03-31 2018-12-31	2019-06-30 2019-03-31	2019-09-30 2019-06-30	2019-12-31 2019-09-30
1	NaN	...	-0.024184	-0.012941	-0.005703	-0.006487
5	NaN	...	0.002967	-0.000898	-0.015038	-0.009648
8	NaN	...	0.041851	0.024812	0.002632	-0.001008
11	NaN	...	0.032092	-0.026296	0.005457	-0.043192
15	NaN	...	NaN	NaN	0.187458	0.211594

Table 16 -Excluse NOR Operation

A	B	A XNOR B
0	0	1
0	1	0
1	0	0
1	1	1

Table 18 present a sample of two different restaurants $\boldsymbol{i}$ and $\boldsymbol{j}$. The result from this sample is 2, meaning that these restaurants had the same variation in time two times. Null values present in the data frame were carried through the process and were not considered in the calculations as Table 18 shows.

Table 17 – Operation between restaurant vectors

$\boldsymbol{Quarters_{\Delta}}$	$\boldsymbol{Restaurant_i}$	$\boldsymbol{Restaurant_j}$	X-NOR
2018-09-30 - 2018-12-31	0.025919	Nan	Nan
2018-12-31 – 2019-03-31	-0.024184	Nan	Nan
2019-03-31 - 2019-06-30	-0.012941	-0.087853	1
2019-06-30 - 2019-09-30	0.005703	-0.113156	0
2019-09-30 - 2019-12-31	-0.006487	-0.054166	1

APPENDIX B

Possible values in the TripAdvisor:

Meals: breakfast, brunch, lunch, or dinner.

Dietary Restrictions: vegetarian-friendly, vegan options, gluten-free options, or halal.

Cuisine: a total of 113 cuisine types such as Portuguese, Mediterranean, Italian, etc.
Dishes: a total of 199 dishes types such as Ice Cream, Caviar, Ramen, etc.

Other features: a total of 17 features such as buffet, delivery, parking, music, etc.

Values found in the dataset:

Meals: all four.

Dietary Restrictions: all four.

Cuisine: 98 out of 113 cuisines types.
Other features: a 17 out of 17 other features.

Dishes: 0* out of 199.

Non-specified: 21 non-specified features at all.

* such attributes are likely to be found in the menu or the content of the reviews but are not inputs in the pages.

APPENDIX C

SentScore: -8.23; **Language:** Portuguese

"O pior restaurante desta rua, sem qualquer dúvida. O atendimento é ridículo, os empregados sem trato nenhum, a qualidade da comida é péssima.Para começar, pedimos choco à setubalense como entrada. Pedimos a dose do cardápio, veio apenas o choco, a batata ficou "esquecida". Qualquer setubalense devia ficar envergonhado ao provar este choco. Feito a partir de choco pequeno e polme muito fraco.Para almoço, pedimos maçada de garoupa e polvo à lagareiro. Passados 5 minutos, não havia polvo. Recomendam choco à lagareiro, damos ok. Vieram os chocos, meramente grelhados, o ser à lagareiro ficou "esquecido", aconselham regar em azeite frio. A maçada de garoupa, pedida para 4 pessoas (400 gr de peixe) dava para duas. No restaurante ao lado, um dia pedimos semelhante, a de duas pessoas dava para quatro.A lição foi bem aprendida. Neste restaurante, nunca mais, nem de borla. Uma vergonha um restaurante nesta zona ser tão fraco, péssimo mesmo. Hoje percebi o porquê desta esplanada estar sempre vazia. Experiência a não repetir."

SentScore: -7.14; **Language:** Portuguese

"Estou tão indignada com o que me aconteceu, não dá para dar menos de 1 para poder demostrar o meu descontentamento. Dirige me a este local para comprar uma refeição e as funcionárias eram lastimáveis. Eu tive nojo de comer pela apresentação das funcionárias. Roupa toda suja, encardida, cheias de nódoas impensável pensei que estava num pais de 3° mundo. Muito antipáticas e com uma cara de chateadas e fiquei na dúvida quem é que estava a fazer de papel e de cliente e de vendedor. Inadequadas tentou me enganar nos ingredientes, escolhi uma massa com ingredientes á escolha, tentou enganar me a dizer que já estava completa a massa e faltava me um ingrediente. Este restaurente é um atentado a saúde pública em todos os sentidos desde as funcionárias mal criadas, com ar de "nojo", aborrecidas, chateadas, contrariadas, á falta de higiene por parte das mesmas, questionando o acondicionamento dos alimentos. deixa muito a desejar. Não aconselho a NINGUÉM."

SentScore: -6.77; **Language:** Portuguese

"'Mau desde o inicio ao fim. Balcões sujos e desorganizados. Para fazer o pedido, demorou mais de 15 minutos. Aqui a culpa não é só do empregado, parece-me que falta

gente. Mas simpatia do mesmo, ZERO.Mas foi a partir daqui que tudo piorou. Provavelmente pedimos algo muito complexo : Imperiais e pregos em Pão!As imperiais vieram "mortas". Pedimos para trocar. Vieram exatamente iguais. Inconcebível.Quando vieram os pregos , que pedimos que 2 deles viessem mal passados, estavam os 3 iguais. Bem passados, secos , maus! Um dos piores pregos que comi na minha vida. Aliás, que não comi, porque estava intragável.E não é exagero. Após ter pago, decidi confrontar o empregado se ele achava que o que nos tinha servido estava em condições, até porque nunca se ofereceu para melhorar nada. Ao que nos respondeu que "estava muita gente" e que " para a próxima poderá correr melhor". É logico que nunca haverá uma próxima porque nunca mais lá irei. E espero que este comentário ajude pessoas que lá pensem em ir.Péssimo.'

SentScore: 8.13; **Language:** Portuguese

"Restaurante com uma vista única sobre Lisboa, o Castelo de São Jorge, a baixa pombalina, o rio Tejo. Enfim, um autêntico e requintado miradouro da capital.Uma arquitectura interior muito bem conseguida, numa sala dominada por cores sóbrias, num sábio equilíbrio entre o moderno e o sofisticado, em que o resultado é uma atmosfera acolhedora e intimista. Ambiente acolhedor, nem demasiado descontraído nem exageradamente pretencioso. Serviço correcto, simpático, discreto, atencioso quanto baste.Este restaurante marca pontos em vários requisitos, que me levam a considerá-lo especial: o espaço, com uma decoração sóbria e elegante que lhe confere requinte e discrição na medida certa; o atendimento correcto e profissional, não deixando de ser afável; a vista que proporciona sobre Lisboa e as 7 colinas; e, por fim, mas não menos importante a cozinha baseada na gastronomia portuguesa, de qualidade, diversificada quanto baste e imaginativa na dose conveniente.Na ementa referência para a empada de caça com grelos salteados em azeite de alecrim ou nacos do lombo estufados com lagosta, em que o contraste de sabores resulta na perfeição. No capítulo sobremesas, imperdível o creme rico queimado, açucarado no ponto .O preço ...um pouco caro, justificado pela excelência... e quando é assim o preço não se discute!

SentScore: 7.40; **Language:** Portuguese

"Os pequenos restaurantes em Lisboa são, geralmente, muito bons. E o Chu-Chu não foge à regra. Acolhedor, com televisões, muito bom atendimento com ótima comida e preços muito interessantes. As entradas - pão, azeitonas, queijos - são ótimos, bem como

o vinho da casa. Comi caracóis e um prato chamado massa do lavrador. Excelentes. A massa é deliciosa, vem com diversos tipos de carne, bem quente e com um tempero maravilhoso. Os caracóis são de tamanho razoável e bem temperados. Fica numa rua bem próxima à Avenida Liberdade, próximo ao metrô Recomendo.Os pequenos restaurantes em Lisboa são, geralmente, muito bons. E o Cartaxinho não foge à regra. Pequeno, acolhedor, muito bom atendimento com ótima comida e preços muito interessantes. As entradas - pão, azeitonas, queijos - são ótimos, bem como o vinho da casa. Comi carapaus com batatas deliciosos. Fica numa rua bem próxima à Avenida Liberdade, próximo aos metrôs avenida e marquês. Recomendo."

SentScore: 7.04; **Language:** Portuguese

"Fomos jantar com amigos e encontrámos um restaurante especial. As salas de refeição mantém a original decoração de anos 60/70 mas tudo à volta é novo, desde a cozinha ultramoderna até às casas de banho que foram modernizadas de uma forma maravilhosa.Os empregados foram do mais simpático, acolhedor e discreto que já encontrei.Quanto à comida… Bem, optámos pelo menu de verão do chefe, começando por um amuse bouche muito bom, passando por uma sapateira desconstruída (apenas com as fantásticas partes da sapateira, eliminando todas as partes que não gostamos – cascas, nomeadamente) e acabando as entradas numas fabulosas vieiras (e quando digo fabulosas, é mesmo espectaculares).Depois passámos ao prato de peixe: dourada de mar ao sal que estava divinal, vem inteira para a mesa e é toda arranjada à nossa frente, sobrando apenas uns suculentos lombos de pescada fresca de comer e chorar por mais. No prato de carne, dividimo-nos: metade comeram bife tártaro (uma fantástica carne picada temperada na mesa com os temperos indicados pelo cliente, no nosso caso, todos) e a outra metade comeram um lombinho de vitela (a carne derretia-se na boca).Toda a refeição foi acompanhada primeiro por aperitivos, depois por um excelente branco, passando por um vinho tinto maravilhoso e acabando num moscatel roxo.Acabámos com a sobremesa Caravela, uma deliciosa combinação de massa filó caramelizada, gelado e doce de ovos, enfim, uma delícia.A acompanhar o café, uns mini miminhos deliciosos.É um restaurante para ocasiões especiais, almoços de negócio e afins dado ser bastante caro (superior a 50€/pessoa) mas face à qualidade de toda a experiência, recomendo vivamente.Definitivamente, temos de lá voltar para experimentar o polvo!"

SentScore: -5.64 **Language:** English

“It was our last night in Lisbon it was getting late and we were walking down the street. An older gentleman kind of roped is in to eating there. I was really hesitant because I know not to eat at a touristy place but he was already pushing tables together for our party of 6. I felt bad so we decided to try it. Worst decision ever! It took close to an hour to bring out the food. By the time they brought the food we were starving! My 2 daughters and I ordered a salad and seafood soup. The soup smelled so bad of rotten fish I almost vomited. I was so hungry I decided to taste it. The taste was even worse than the smell. I sent it right back. They still charged us for the rotten soup even though we didn't touch it. It was just an overall horrible experience. We just wanted a good fast meal. Instead it was a disgusting all nighter. We left exhausted, frustrated and starving... and to top it off, it was the most expensive meal we had in the whole country of Portugal. So disappointed!“

SentScore: -4.70; **Language:** English

“Horrific experience and the worst customer service I've encountered.Ordered two dishes specifying that I have a severe allergy. The dish turned up and upon trying clearly established that the ingredient had been included which caused me to spit it out much to my embarrassment as it would have caused a severe reaction otherwise.The waitress albeit a little incompetent replaced the dishes with the ingredient removed.The main issue occurred at the till.A middle-aged greying hair manager or owner proceeded to verbally abuse me and my group when we asked why we should pay for food I could not eat. He was abusive, rude and aggressive, trying to make us pay. He clearly treats his staff terribly and is a horrific manager and person. Assuming we didn't understand Portuguese he insulted us, then told us we were not welcome in his establishment in the future. We would avoid it like the plague. Do not go here - plenty of other charming places nearby."

SentScore: -4.70; **Language:** English

“Myself and 5 family/friends visited this restaurant on our last night. We were hustled in there by a guy on a street corner. That should have been a warning. The staff were rude and indifferent. The food was less than average and not very hot. The woman who seemed to be running the place was vile. We called her Cruella. We tried to get the bill but we was ignored so got up to go to the desk to pay. As I was explaining to the man there, a burly looking woman barred the door with her arm as if we was about to leave without paying!!! We was also charged per person for the entertainment which although not to

my taste was ok, but this was not explained to us when we went in. The bill was more than double what we paid anywhere else but for sub standard food. DO NOT under any circumstances make the same mistake as we did. AVOID this dreadful place at all costs. We all said we had never come across such rude, ignorant, intimidating staff."

SentScore: 8.80; **Language:** English

"So, we've eaten sushi in many countries and aside from Japan we have to say that this place is one of the best ones we've had. They have real wasabi - which is fantastic. I love that they have a contemporary menu for those that don't enjoy sushi. Ambience: We sat on the patio - it was perfect. Almost felt like you weren't outside. They played wonderful Jazz music at just the right volume. The place settings were gorgeous. A+++Food:As stated above - WOW. 5 star for sure. To start we had Gyosas. They were the lightest, fluffiest gyosas we'd ever had. Perfectly dripped with terayki and sesame. Next were the wontons - great but didn't really enjoy the sauce that came with it - definitely better naked. Next were the SHRIMP TEMPURA - WOW. So my husband refused to try shrimp until he saw the look on my face. He had it and was blown away and is now a fan of shrimp. They were so juicy, fresh and perfectly cook and the black garlic mayo was the cherry on top. We also had the california and spicy rolls. Yup - so perfectly prepared and beautifully presented - some of the best sushi we've had outside of Japan. DESSERTS - I had the Earl Grey Crème Brûlée with cinnamon and biscuit ice cream. Hands down the best dessert I've ever had AND best crème brûlée I've ever had. My husband had the marscapone supreme and love it.Service:Our waiter was phenomenal. Spoke English very well and was comfortable making suggestions on what to have. He checked in with us just the right amount of times and had wonderful conversation with him. So on top of great service - the food was out of this world. Well worth the price - with tip for 2 of us was 120. Thats 3 starters, 2 rolls, contemporary main with a side, 2 desserts, double of single malt whiskey (served properly) and a cocktail. Personally, for the quality we thought that was a bargain. You would be missing out if you love sushi and didn't go here."

SentScore: 8.68; **Language:** English

"I'm so glad I found this restaurant through the Happy Cow app! Simply amazing! Let's start off with the service as that's equally as important as the food...The minute you walk in your greeted by friendly, amazing staff who make you feel right at home. The service was fantastic during my whole time I was in the restaurant. They also have a lovely

atmosphere with tasteful decor. I started off with an Apple Cider and the Spicy Cheese Dumplings. Both were great! They serve the apple cider with freshly diced apples in the glass and a slice of lemon - nice touch and it did great adding just that bit more flavour! The Spicy Cheese Dumplings were delicious! Crispy & crunchy on the outside and cheesy on the inside. Really lovely flavours. If your looking for some comfort food then order these! For the main course I tried the Kong burger with bacon and the beyond burger patty. Loved it!! It came with just the right toppings and a good portion of them as well. The bacon was a nice touch and gave it a gentle smoky flavour. Well balanced burger. It also came with fries and to my surprise they were not only freshly cut but they were also nice and thin! Very tasty and cooked just perfect! For desert I ordered the chocolate cake and wow....this was one of the best I've ever had! Not only is the cake perfectly baked with delicious nuts but they put this warm chocolate sauce on top which was crazy good - fantastic balance!! I couldn't help myself and I also ordered the tapioca cake for take away which I have not eaten yet but I can't wait to try it - it looks just as good as the chocolate cake. If you've never eaten here or are just browsing - definitely come here! The food, the service and the atmosphere is amazing!"

SentScore: 9.62; **Language:** English

"We were recommended Grei by the concierge in our nearby hotel and what a recommendation! It was really excellent on all counts and we loved it so much we went back on our last night in Lisbon! It's located in a quiet residential area, but is an absolute delight! It's decor is modern and contemporary in style with shades of grey - obviously - but it's the food and service where Grei excels! The service we had on both evenings was superb! Our different servers were very friendly, warm, helpful and attentive, but professional at all times, with great English. But it's the food which makes Grei stand out - it was excellent! You are served homemade breads with different butters/dips - all great - before your starter. My wife went for the onion soup, which she said was one of the nicest she'd ever tasted - it came with a puff pastry topping! - and I had Ravioli Foie Gras with diced pear and chocolate sauce - yes, really! - and it was superb! My wife selected the duck for her main course and she said it was cooked perfectly and she loved it! I went for the Lobster Tail and Prawn Risotto and can honestly say it was one of the nicest risottos I've ever tasted! Superb !We couldn't eat dessert we were so full, but the coffee is also excellent. The Portuguese wines recommended were excellent and we had a local Lisbon wine, Francos Reserva, on our first visit and a superb Douro Duvalley 2011 on

our second visit. Excellent selections by the Grei team! On our second visit I ordered the monkfish soup starter, but they brought onion soup instead. I was happy with that, but the waiter apologised profusely and insisted on bringing the monkfish soup - for both of us, even though my wife had selected and been presented with her mussels dish! Now that's service! We both went for the delicious risotto as our mains, and again it was superb !On both visits we were given a complimentary glass of port with our coffees, which was a nice touch .We were told the waiter came from the Azores and he makes Grei stand out from the crowd for sure! I cannot recommend Grei highly enough! Superb food, great wines and excellent service in a warm relaxed atmosphere! What's not to enjoy!"