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Exploring the Impact of Negative Words Used in Online Feedback in Hotel Industry: A Sentiment Analysis, N-gram, and Text Network Analysis Approach

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ABSTRACT

This study examines the words and situations that trigger and those that do not trigger a hotel response when customers post negative online feedback. The research explores, through sentiment analysis, bigrams, trigrams, and word networking, the valence of online reviews of five important hotels in Las Vegas. Only the feedback that has been categorized as negative by the algorithm is selected. In correspondence to this feedback, the existence of answers from the hotels is checked together with the response style. While the negative valence of the feedback can represent a mixture of subjective and objective emotions, there are common features present in their expression. On the responses side from the hotel, not all the reviews receive attention. As such, the negative feedback words are extracted and separated into those that belong to reviews that obtain a response and those that do not. The replies are standardised by following an established pattern. This paper aims to contribute to a prominent issue in tourism that is little tackled: responses to feedback. The findings may help the hotels' management explore different paths to improve their services and responses alike. Behavioural marketing researchers might want to use these results to confirm the existence of such patterns in different datasets or situations.

JEL classification: L83, M31, Z30

Keywords: sentiment analysis, tourism, hotels, marketing, customer's opinions.

1. INTRODUCTION

Feedback is important in the hotel industry because it helps hotels understand the expectations and satisfaction levels of their guests, as well as, identify patterns in reviews as well as areas for improvement and make necessary changes to enhance the guest experience (Torres et al., 2015). A consistent part of the GDP of many countries is given in general by the service industry and the tourism industry in particular (Bazargani & Kiliç, 2021). The quality of these services is sometimes hard to assess. Nevertheless, in the last years, with the introduction of the possibility of customer satisfaction expression through direct feedback, the results are mesurable. These results can be

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expressed in a numerical form, such as several stars to encode an experience, or as a message text for future visitors and/or hotel management. The number of stars may be variable, but they can be associated with a Likert scale, defining a terrible experience with a star on a particularly pleasant one – with five stars. This assignment, of course, is subjective, depending on several factors (Willits et al., 2016). Still, negative feedback is considered when the stars number of given ranges from 1 to 3 and positive from 4 to 5 (Proserpio & Zervas, 2017). Dissatisfaction arises when there are discrepancies between our own expectations and the perceived reality. A direct consequence of the customers' negative feedback should be a drive for an improvement in service quality, so perceived as an opportunity, but sometimes it is perceived as a threat that needs to be silenced.

There are several approaches to dealing with criticism in feedback. It was seen that any answer is better than no answer (Esmark Jones et al., 2018). One approach, which seems to be preferred, is to adopt a structured answer that follows the 10 moves scheme: express gratitude, apologize for sources of trouble, invitation to a second visit, the opening pleasantries, proof of action, acknowledge complaints, refer to customer reviews, closing pleasantries, avoidance of reoccurring problems, solicit response (Zhang & Vásquez, 2014). Other approaches follow a similarly structured answer pattern (Sparks, 2001). Inappropriate and untimely responses (Davidow, 2003) to the e-WOM (electronic Word-Of-Mouth) of dissatisfied customers can lead to losses in monetary terms and credibility.

This paper's main purpose is to identify, in negative feedback, the words that lead an accommodation unit to respond and those that do not trigger a response. The analysis will be done with the help of sentiment analysis, which is part of the Natural Language Processing (NLP) ecosystem.

The dataset in this work was obtained from the Unwrangle blog (Singh, 2021) and was originally sourced from Yelp.com. There are a total of 6 Las Vegas hotels: Bellagio, The Cosmopolitan, M Resort SPA Casino Henderson, MGM Grand, South Point Hotel Casino and SPA and The Venetian, but only the first 5 were considered because, although The Venetian had many reviews, the responses to these reviews were only 2. The hotels are enormous and well-known in the U.S. and abroad as well. The complete dataset consists of more than 20,000 feedback reviews starting from 18th October 2004 until 22nd April 2021.

In the realization of this study, the R programming language (R Core Team, 2022) was used, as was the RStudio interface (R Studio Team, 2022). Additionally, the code was written by the author. The study makes use of NLP, a branch of Artificial Intelligence.

2. LITERATURE REVIEW

In any service industry, there is a link between the quality of service and customer satisfaction. Depending on how the perceived service is delivered, customers react, and their reaction is subjective and objective alike. This is also valid in tourism, especially in the hotel industry, and is deemed useful to improve service quality (Li et al., 2013). The customer is the main player that can be considered a limited empowered influencer. This definition arises because based on the feedback they give, they have the power to influence and thus convince hotel managers to make changes, sometimes structural, that voice from the outside of the accommodation unit and concern the accommodation unit based on a short-term experience. Customer opinions expressed through publicly available feedback might be more subjective than objective though (McAuley & Yang, 2016). In the hotel industry, an ideal customer would return, and physical attributes play a key role, exceeding one of the services received (Worsfold et al., 2016). Overall, when tourists wanted to book a service (be it a hotel room or a guided tour) in a new place, they would read online reviews and make decisions upon that (Xiang et al., 2015). The similarity between the reader and the reviewer can influence the decision process (Chan et al., 2017).

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2.1. Negative Online Reviews

Even long before the internet era, WOM was used to recommend products because buying something that had a certain cost could have been considered a risky operation. It is understood that sellers were affected if bad WOM was spread (Cox, 1967; Woodside & Delozier, 1967). In marketing, customer evaluations and complaints need to be properly addressed because they involve satisfaction and, more importantly, trust (Tax et al., 1998).

E-WOM is by now an established concept, it represents a transfer of classical WOM onto the internet. When booking a (new) hotel room, after the price, tourists look for other peoples' experiences in that hotel, and e-WOM is expressed through online reviews). These comments can have a strong impact on how and what other people choose (Filieri & McLeay, 2014). Online reviews have a strong influence and can determine the income flow of a company, no matter if touristic or not. Accommodation-related comments may be found on booking platforms such as Booking.com or Tripadvisor.com and, depending on these platforms, people might have a different attitudes towards a hotel brand image, so each of them influences peoples' choices in a separate way (Borges-Tiago et al., 2021). Feedback comments are found on other platforms as well, such as an another well-known one is Yelp.com, which hosts opinions on several businesses, including accommodation structures.

Negative comments usually have a greater impact in cases where there is little knowledge of a product, there is an elevated risk due to purchasing or when the price is incredibly competitive and advertised as the lowest (Chaterjee, 2001). For a business, the biggest issue is that comments on products influence sales (De Maeyer, 2012), and this also happens in the hotel industry (Gavilan et al., 2018). Feelings about a touristic experience, for example, are not shared only through a final review and a rating but are also shared via social media channels such as Facebook or Instagram, and can amplify the effect. This can have a strong impact on the perceived experience (Kim et al., 2013). In case of problems, it is not always the business's fault. Negative reviews might be written impulsively due to a dispute with the staff. Oftentimes, these are due to the customers' incivility and the way the employees deal with these issues is crucial (Zhu et al., 2019). On the negative complaints side, before posting them, customers try to solve their problems with the staff. If the complaints are not solved or are dealt with poorly, then the negative feedback will be posted online (Sparks & Browning, 2010).

Negative feedback needs to be dealt with. Lee and Hu (2004) have seen in their study that around one out of five negative results received a response from the hotel management. In some cases, hotels do not respond at all, and most responded to negative feedback more than positive ones (Park & Allen, 2013). Some hotels reply to positive feedback by repeating words of appreciation from the customers. But the most challenging task is to answer negative feedback, which contains service failures, misunderstandings, or even false claims by the customers. Another issue is on what channel to address negative feedback. Some use the same online tool, while others choose to follow up privately (Chen et al., 2016).

2.2. Text Analysis in Reviews

There are countless papers in the specialized literature on automatic text analysis of reviews. Many focus on sentiment analysis (for example, Berezina et al., 2016; Collandon et al., 2019; Dadhich & Thankachan, 2022), other on topic modeling (Büschken & Allenby, 2016; Park & Liu, 2020; de Oliveira et al., 2021) and text summarization (Zhan et al., 2009; Raut & Londhe, 2014; Sathiya et al., 2022). There is also interest in automatically analyzing negative reviews (Lee et al., 2017; Ali et al., 2021).

But there is no specific analysis on what makes the management of a hotel respond or not to negative feedback, or what are the words (and situations) that might trigger a response.

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3. MODEL SPECIFICATION AND DATA

Dealing with huge volumes of text is daunting, hence the need for dimensionality reduction. The following steps were applied to the feedback review(s), here called only review(s), and response(s) to feedback, here called response(s). Both underwent the following pre-formatting steps. Initially, with the help of regular expressions, the extra HTML characters present in the text were removed.

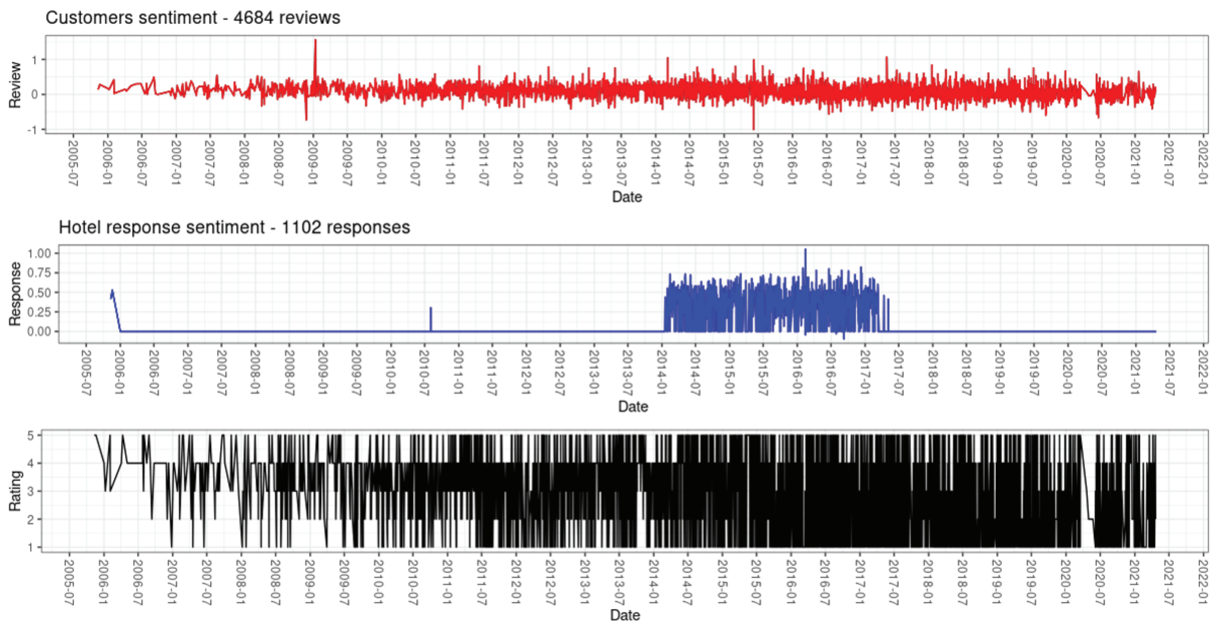
The polarity of the reviews is computed by considering their sentiment analysis score with the help of the *sentimentr* (Rinker, 2021) package. Firstly, all text is tokenized at the sentence level and the overall sentiment value is averaged for each review. Then, a polarity separation into positive and negative is performed.

For the sake of clarity, the MGM Grand Hotel reviews were taken as the main case study, but all of them underwent the same procedure. MGM happens to be the largest single hotel in the world (C.A.R. Team, 2020).

Figure 1 shows, on a timeline, the number of reviews (4,684) and their sentiment. The baseline 0.0 indicates neutrality in sentiment, above that limit – positivity and below – negativity. It can be noticed that the responses are limited to a certain period, between 2014 and 2017. Their number is 1,102. Again, we have positivity, neutrality, and negativity in the sentiment of the text of the responses. The bottom part of the figure represents the rating, expressed in stars from 1 to 5 for each review.

Figure 1

Sentiment distribution of reviews, responses, and rating, MGM Grand Hotel



Source: Author's computation.

As can be noticed, there is a period where the responses are consistent, and those periods are considered for computation. Table 1 shows the total reviews in the dataset, the number of computed negative reviews, the number of responses and the number of responses to negative reviews. The number of negative reviews is calculated by selecting feedback that has (i) negative polarity and (ii) a rating that is less than or equal to 3 (Proserpio & Zervas, 2017). Not all negative reviews get a response, but there are certain common characteristics to which they get one, and which is the topic of this research. Be aware that the accommodation unit also responds to positive feedback, but this is not the object of the current study.

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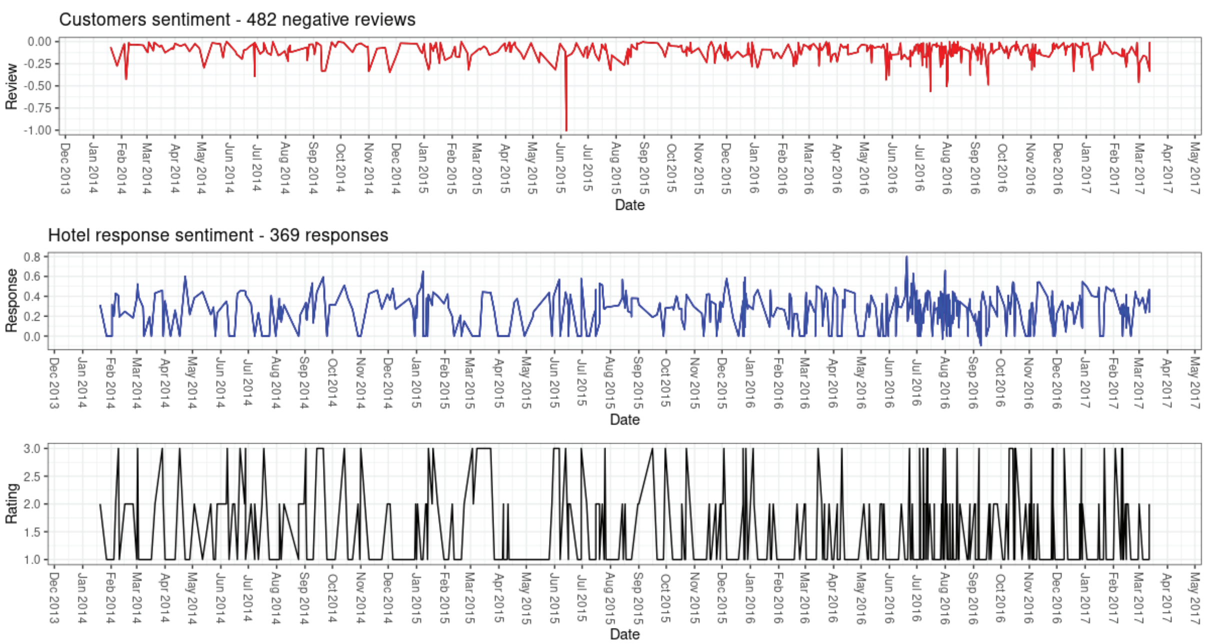
Table 1
Reviews and responses distribution

Hotel Name	Reviews	Negative Reviews	Responses	Responses to Negative Reviews	No Responses to Negative Reviews	Period
Bellagio Hotel Las Vegas	3,884	178	611	128	50	07/01/2015 – 15/03/2017
M Resort SPA Casino Henderson	1,343	72	222	34	38	01/03/2018 – 16/04/2021
MGM Grand Hotel Las Vegas	4,684	**482**	1102	**369**	**113**	19/01/2014 – 14/03/2017
South Point Hotel Casino and SPA	1,920	254	977	164	90	13/02/2014 – 10/03/2020
The Cosmopolitan of Las Vegas	5,040	221	232	104	117	02/05/2017 – 08/10/2020
The Venetian Las Vegas	4,148		2			–

Source: Author's elaboration.

Figure 2 shows, again on a timeline, exclusively the period of the 482 negative reviews, between 19/01/2014 and 14/03/2017, which obtained 369 responses. It results in major clarity that the customers' sentiment tends to the negative side, with respect to where the 0.0 baseline is while the hotel responses also include positivity elements. The ratings follow the sentiment of the reviews, meaning that where there is negative feedback, the ratings are low.

Figure 2
Responses selected period, MGM Grand Hotel



Source: Author's elaboration.

Further on, the bag-of-words model (Zhang et al., 2010) was applied to get the necessary dimensionality reduction. In the pre-processing phase, stopwords, numbers, and punctuation were removed, white space was stripped, and Porter's stemming (Jivani, 2011) was applied. The function *sentiment_words*, from the package *sentimentr*, was used to extract the negative words from the negative reviews that obtained a response and the negative reviews that did

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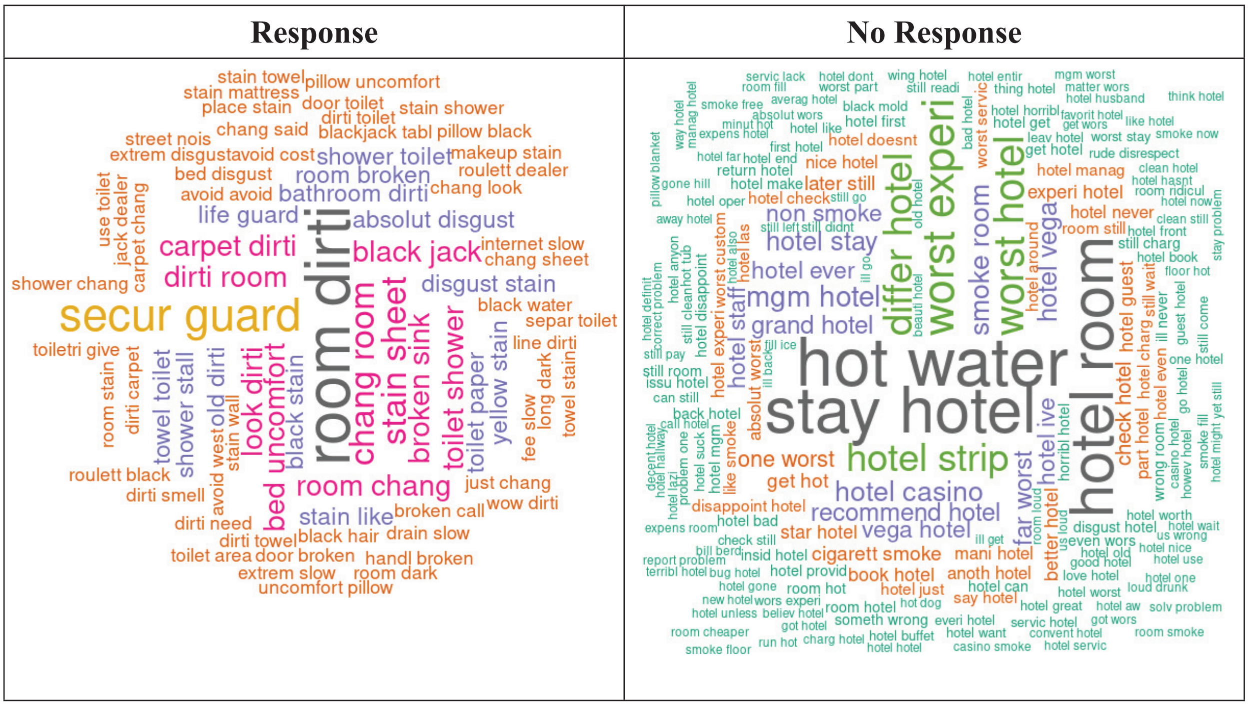
not obtain one. The most negative 20 words out of 588 from the former and 20 out of 368 from the latter ordered firstly by negativeness and then frequency are as follows. Reviews with a response: disappoint (53), issu (45), rude (43), complain (29), disgust (24), drain (18), wast (18), unfortun (15), nasti (14), complaint (14), outdat (13), miss (13), crap (12), nois (11), gross (10), p*ss (9), scream (9), mess (8), wtf (7), ignor (7). Reviews without response: rude (24), disappoint (23), issu (20), disgust (7), crap (7), nois (6), complaint (6), mess (6), hung (5), bug (5), b (4), miss (4), f**k (4), knock (3), outdat (3), gross (3), shame (3), p*ss (2), error (2), idiot (2). All words appear in their stemmed form.

4. EMPIRICAL RESULTS

As was assumed, there are words that appear only in reviews that obtained responses, words that appear only in reviews that did not obtain a response and words that appear in both. Further on, applying the same principles to all the datasets and intersecting the common words, the following results were obtained. The words that appeared exclusively in reviews with responses, ordered by their polarity score: disgust, nois, hung, unprofession, crappi, insult, stain, hell, dirti, broken, uncomfort, annoi, mediocr, excus, dark, avoid, overpr, fault, empti, stall, difficult, embarrass, toilet, black, slow, hang, dealer, guard, odd. The words that appeared exclusively in reviews without responses, ordered by their polarity score: miss, f**ck, shame, unfortun, ridicul, problem, s*ck, wors, wrong, tire, lack, disrispect, limit, ill, cheap, smoke, loud, hot, expens, stuck, hit, treatment, incid.

The use of bigrams gives a better understanding of specific topics in text analysis, for example for violence-in-online-discussions detection (Hammer, 2014). Figure 3 depicts the bigrams obtained from the words that appeared exclusively in the negative reviews that obtained a response, on the left, and the bigrams obtained from the words that appeared exclusively in the negative reviews that did not obtain a response, on the right, in this example applied to the MGM hotel reviews.

Figure 3
Bigrams, MGM Grand Hotel, Response and No Response



Source: Author's elaboration.

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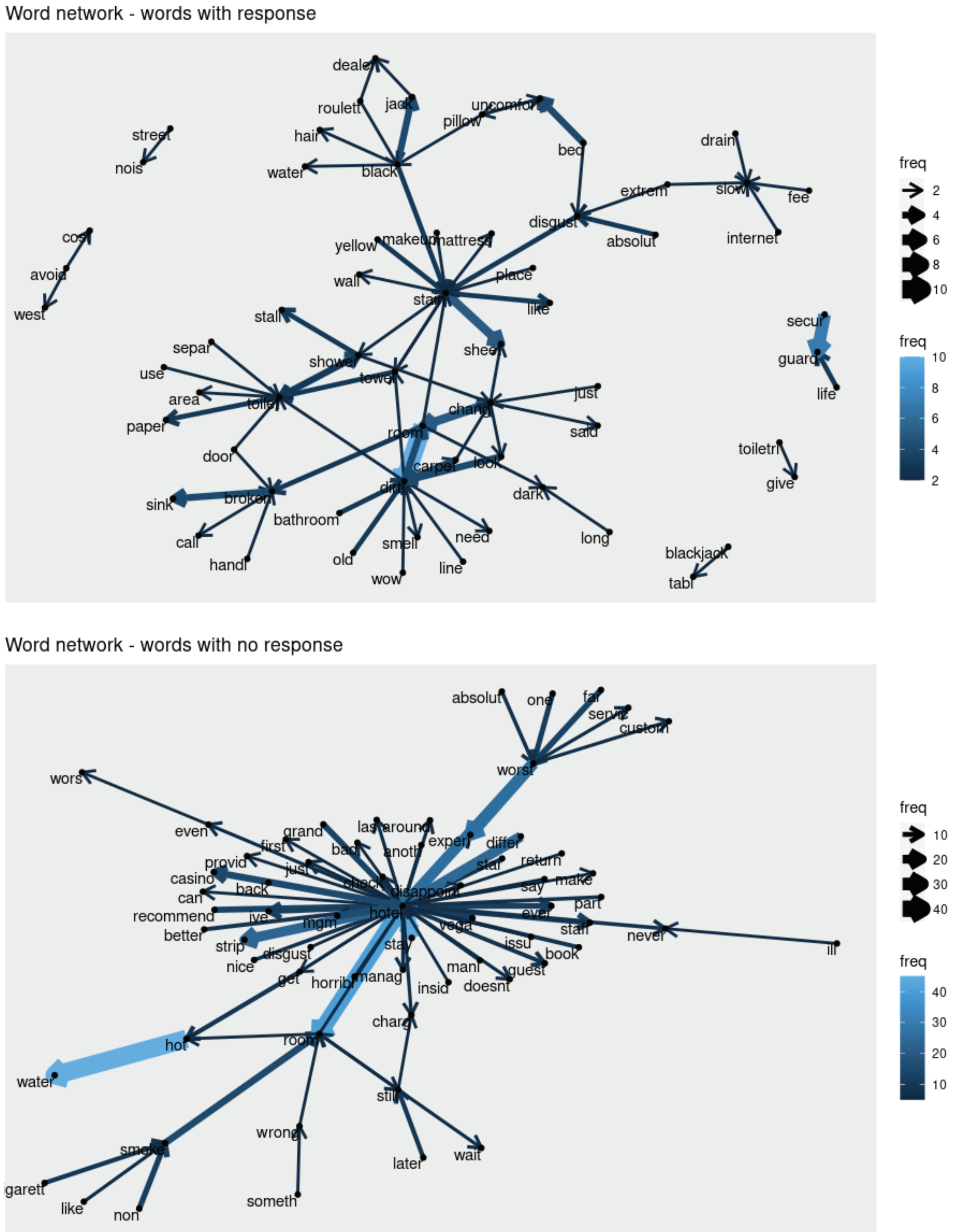
Text classification through word networks can give a further understanding of specific topics in the datasets (Yan et al., 2020.) Figure 4 at the top presents a word network of the shared words in the reviews that obtained a response and at the bottom, it presents a word network of the words in the reviews that did not obtain a response. Both networks are related to the MGM hotel.

Figure 4

Word Networks, MGM Grand Hotel, Response and No Response

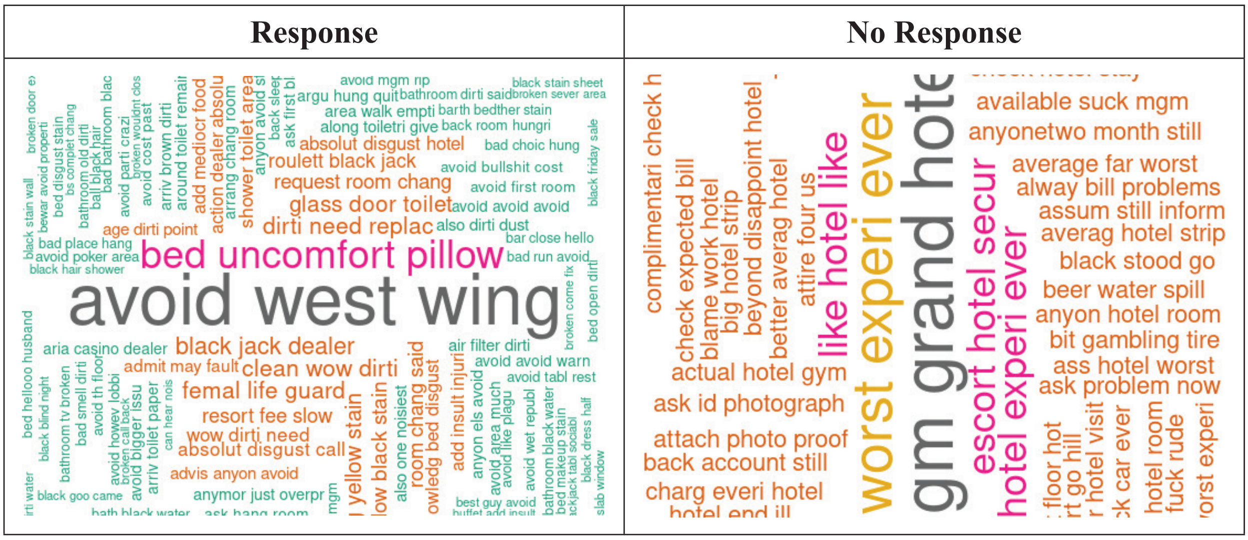


Source: Author's elaboration.

Bigrams offered a good but partial view of the reviews-responses dyad. For this reason, the use of trigrams can be used to obtain more information such as detecting emotion (Desmet et al., 2013) in sentences and can give a more fine-grained understanding of the underlying text. Figure 5 shows the same structure as Figure 3 but represents trigrams instead of bigrams.

Figure 5

Trigrams, MGM Grand Hotel, Response and No Response



Source: Author's elaboration.

The common words for all the responses in any hotel are represented by the following single words expressed in order of their frequency: sincer, apolog, regret, hope, resort, servic, stay, feedback, thank, future, experi, guest, issu, pleas, provid, recent, impro, share, appreci, forward, regard, time, review, can, inconveni, opportun, assur, team, guests, manag, consid, take, contact, experience, sure, strive, import, ensur, best, like, hear, servic, detail, pool, casino, inform, along, soon, attent, direct, hesit, rooms, sorri.

Note that although the common negative words which appear in feedback that obtain a response and those that do not obtain a response are unique for each type but for all hotels, the bigrams, trigrams, and implicitly the word networks may yield different results, depending on the individual hotel they are applied to.

5. CONCLUSIONS

This work covers a field to which is given truly little attention: responses to feedback in online reviews. While how to respond is tackled (Sparks et al., 2017), when feedback obtains a response is an uncharted territory. From the results, the feedback that triggered a response happened when there were specific words involved (see the beginning of Section 4). Especially U.S. customers are keen on cleanliness and its subcategories, such as general, guest room, toilet, shared areas, and others as also researched (Au et al., 2009.) Bigrams such as "room dirti," "stain sheet," and "bathroom dirti" are just a few examples. Another crucial factor is represented by the interaction with customer service for changing rooms due to a lack of cleanliness or dislike of the guest room. More precisely, a response to criticism arises when customers advise future customers to "avoid" the hotel. Other reasons to complain and obtain a response are when the waiting time is too long, when a reservation is dealt with poorly, the personnel is targeted as being incompetent or rude and the value for the money is perceived as inadequate. When the customers use profane/vulgar words, complain about the smoke smell, about something too loud, about the hot water, or

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when the experience in the hotel is perceived as “worst”, will not obtain a response. Smoking is a particular topic, which can be seen in the network graph, Figure 4 at the bottom. The smoking ban in the U.S. is duly reinforced to reduce the smoking population (for example, see Bird et al., 2020) but not at Casino Resorts, albeit many non-smokers visit casinos (Sakevich, 2016). Dissatisfaction and potentially negative e-WOM for future readers can be mitigated through responses. In the case of the MGM hotel, there seems to be a trigram advice such as the “avoid the west wing” zone that is addressed by the management, unlike the “hot water” issue that receives no response from the structure. These things were specific to this accommodation unit, but the negative words were common to all of them. The network analysis gives more information about how words are grouped, mostly in smaller or larger topics like comfort, cleanliness, and services (Au et al., 2009), and represents how (in this case negative) words relate to them. Interestingly, the responses are remarkably similar and standardized. They include apologies, thanks for the feedback, regret for the mishaps, and the wish for the customer to return with a promise that in the future the problem will be solved and the customer’s experience will be improved. A similar observation was made by Alrawadieh et al. (2019). They are eager to follow up on the issues but through emails, out of other potential tourists’ eyes.

5.1. Managerial Implications

Automatic text analysis can bring to the forefront patterns of reviews that could elicit a response when these sensitive situations are expressed with specific words. Obviously, these are crucial for the businesses’ reputation. Following such an analysis, management and marketing departments could pay major attention to preventing conflictual situations, learn how to properly deal with them, and leverage the points of strength. Feedback leads to specific actions on the side of the hotel (Assimakopoulos et al., 2015). There is no need for the management to read all the reviews, automation saves time and money. Management can look for the existence of negative words in feedback to improve their reputation.

5.2. Limitations and Future Research

More research needs to be done with bigger and more complete datasets that contain responses and different services or products. For each industry field, there might be different word triggers, but the algorithmic steps can be automatized in the same manner and are identical to the ones used in the case of this study. An interesting follow-up would be an empirical study on how to answer properly in cases where a hotel would typically not respond.

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