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# Enhancing Restaurant Management through Aspect-Based Sentiment Analysis and NLP Techniques

Paulo Carrasco<sup>a\*</sup>, Sandra Dias<sup>a</sup>

<sup>a</sup> School of Management, Hospitality and Tourism (ESGHT), Algarve University, Faro, Portugal

## Abstract

This paper presents a flexible and automated methodology for extracting and analyzing customer sentiment in the restaurant industry through online reviews. The proposed approach is evaluated on a sample dataset of 1000 reviews, as well as applied within an accompanying web application that utilizes a large corpus of 880,000 reviews from 1581 restaurants located in the Algarve region. By leveraging advanced Natural Language Processing (NLP) techniques such as Aspect-Based Sentiment Analysis (ABSA), this study seeks to accurately classify customer sentiments according to specific attributes related to food quality, service, ambiance, pricing and location. To assess its performance against human classification processes, the results demonstrate that the proposed methodology effectively replicates them with three alternative approaches for attribute extraction and classification being presented; among which BART model consistently outperforms DeBERTa while ChatGPT achieves highest F1 Score. Named RestMON Algarve, the developed web application will allow restaurant managers to extract and analyze customer sentiment from online reviews; track attribute evolution over time; compare performance between competing restaurants - thus providing relevant insights into enhancing customer satisfaction levels leading towards overall success in hospitality industry.

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## 1. Introduction

The Algarve region is widely acknowledged as a popular tourist destination for its sun and beach attractions, but there has been an increasing appreciation of its gastronomic potential. The National Strategic Tourism Plan [1],[2]

\* Corresponding author. *E-mail address:* [pcarras@ualg.pt](mailto:pcarras@ualg.pt)

emphasizes the importance of promoting Portuguese cuisine, creating renowned dishes, and improving the quality of catering establishments to shape the economic and tourism landscape of this area. Consequently, dining experiences have become a major attraction for tourists worldwide with approximately one-quarter of global expenditures allocated to food and beverages [4]. Therefore, effective restaurant management is essential in ensuring customer satisfaction which will lead to successful businesses [5]. In recent years online reviews from platforms such as TripAdvisor have become increasingly important when understanding customers' opinions on restaurants due to their ability to share recommendations with others [6],[7].

By leveraging advanced Natural Language Processing (NLP) techniques such as Aspect-Based Sentiment Analysis (ABSA), restaurants can gain deeper insights into customer sentiments along with areas that need improvement [8], enabling them to develop more efficient strategies. This technology involves using semantic embeddings within high dimensional spaces which allows us capture complex meanings expressed by customers through online reviews; thus, providing detailed interpretations regarding sentiment analysis within the hospitality sector. Furthermore, managers can make informed decisions based on comprehensive data analysis leading towards improved restaurant management practices. Recent advancements in NLP word/sentence embedding capabilities have had significant impacts across various industries including hospitality [9].

The next two subsections, 1.1 and 1.2, describe the research objectives and the contributions of this paper. The rest of the paper is organized as follows: Section 2 provides an overview regarding relevant literature concerning Electronic Word-of-Mouth (EWOM), key attributes pertaining to restaurant experiences and aspect-based sentiment analysis; Section 3 outlines the methodological framework employed during this research project; Section 4 details results obtained through experimentation; Section 5 introduces a custom developed web application used for monitoring purposes and concluding remarks are presented in section 6.

### *1.1. Research objectives*

This research seeks to develop a flexible and automated methodology for extracting complex and valuable information related to customer sentiment in the restaurant industry, reflected in online reviews. This approach focuses on eleven attributes associated with food quality, service, ambiance, pricing and locale; furthermore, it aims to evaluate its performance against human classification of these attributes so as to determine whether an automated process can accurately replicate the manual analysis of customer sentiment within defined parameters.

### *1.2. Contributions*

The primary contribution of this study is the development of an automatic method based on a generic Natural Language Inference (NLI) classifier that has been designed with flexibility in mind so as to be applicable not only within the restaurant sector but also across other areas within hospitality services. Additionally, this paper presents a prototype web application which applies said methodology onto 880 thousand reviews from 1581 restaurants located throughout Algarve region - Portugal - thus demonstrating its feasibility when applied at scale.

## **2. Related topics**

### *2.1. eWOM - electronic Word of Mouth*

In the current digital age, electronic Word-of-Mouth (eWOM) has become a fundamental element of consumer communication, encompassing exchanges and dissemination of opinions among consumers through online platforms such as review sites, forums and social media [10]. In particular within the tourism sector, eWOM is particularly significant due to its ability to provide insight into customer attitudes, experiences and intentions [11]. Within hospitality contexts such as restaurants in particular this impact is further amplified by several factors:

- **Information Source:** Modern customers often turn to online sources for research prior to making dining decisions; eWOM facilitated by reviews and ratings provides valuable information regarding food quality service levels and overall dining experience at any given restaurant.
- **Trustworthiness and credibility:** Consumers tend to place more trust in peer opinion than promotional content from restaurants; thus, eWOM becomes an extremely credible source of information that significantly influences consumer decision making processes.
- **Increased visibility:** The presence of eWOM increases visibility for restaurants on the web; when customers post reviews or share their experiences it can improve search engine rankings which may attract potential new customers.
- **Customer feedback mechanism:** Reviews serve as a useful feedback mechanism for restaurants allowing them understand customer expectations preferences while also demonstrating commitment towards achieving satisfaction with services provided.
- **Impact on sales:** Positively received word -of mouth can lead increased sales via attracting new custom whilst encouraging repeat patronage; conversely negative comments have been known deter potential clients, highlighting importance superior dining experiences must be offered if success desired.

Given these considerations it is essential that proactive strategies are adopted when managing eWOM; this could involve motivating satisfied patrons share their positive encounters online, responding constructively criticism expressed in reviews plus utilizing feedback enhance service quality ensure highest possible level customer satisfaction achieved.

## 2.2. Measuring a restaurant experience

The connection between customer satisfaction and positive customer behaviors and intentions highlights the significance of recognizing the attributes that are in line with customer expectations and their correlation to favorable responses [12]. Therefore, it is beneficial for restaurants to develop strategies that enhance their competitive advantage.

Given the association between perceived quality, customer satisfaction, and customer behaviors, there is a need to investigate how attributes affect their satisfaction. These attributes are closely related to consumer satisfaction and their subsequent reviews of restaurants; however, determining these attributes presents a challenge due to conflicting opinions among researchers regarding the number and type that should be taken into consideration when evaluating restaurant quality [13].

A considerable number of studies have identified meal experience, food and beverages, service, ambient, price, and value as essential factors for customers when selecting a restaurant [14]. While food quality is generally accepted as the most influential attribute, other factors should not be disregarded. Pantelidis [15] suggests that despite numerous studies being conducted on this topic, the primary factors remain uncertain; however, his model indicates that food quality is followed by service quality in terms of importance while ambient comes third followed by price menu and decoration respectively. Pacheco [16] identifies four specific elements: food quality, service, cost-benefit ratio, and ambient concluding that first two are key determinants of overall satisfaction. On TripAdvisor website, food, service, and price are consistently visible features while ambient may not always be so.

The literature on customer satisfaction in the restaurant industry has identified a range of key attributes that are believed to influence the overall dining experience. These include food, service, and ambient, with Liu & Jang [12] additionally proposing quality/price ratio and authenticity (for ethnic restaurants) as important considerations. Food quality can be further broken down into subcategories such as presentation, menu variety, healthy options, taste, freshness, temperature and safety; each of which may have distinct impacts on customer satisfaction. Service quality is a subjective measure that is contingent upon the discrepancy between expectations and perceived performance; it

encompasses not only food quality but also service interactions - Jeong & Jang [17] noting instances where service interactions superseded other factors as the primary attribute for customer satisfaction. Angnes & Moyano [18] along with Mellinas & Reino [19] introduce location as an additional factor to consider when assessing customer satisfaction in restaurants. For this study then, five attribute areas will be focused upon: food, service, ambient environment price and location; these being further broken down into eleven sub-attributes of interest (as detailed in the Table 1).

Table 1. List of Sub-attributes and references.

Sub-attributes	Attributes	References
1. food flavor (+/-)	Food	Tiago et al., 2015 [13]; Pacheco, 2018 [16]; Agnes & Moyano, 2013 [18]; Pantelidis, 2010 [15]
2. food presentation (+/-)		
3. menu variety (+/-)		
4. service hospitality (+/-)	Service	Tiago et al., 2015 [13]; Pantelidis, 2010 [15]; Pacheco, 2018 [16]
5. service efficiency (+/-)		
6. ambiance decoration (+/-)	Ambiance	Tiago et al., 2015 [13]; Angnes & Moyano, 2013 [18]; Pantelidis, 2010 [15]
7. ambiance acoustics (+/-)		
8. ambiance cleanliness (+/-)		
9. price (+/-)	Price	Tiago et al., 2015 [13]; Pantelidis, 2010 [16]
10. locale accessibility (+/-)	Locale	Angnes & Moyano, 2013 [18]; Mellinas & Reino, (2018) [19]
11. locale scenery (+/-)		

### 2.3. Aspect-Based Sentiment Analysis (ABSA) in online reviews

The application of Aspect-Based Sentiment Analysis (ABSA) to assess customer opinions and sentiments in regard to specific aspects of products or services has seen a sharp rise in recent years. This is largely due to the emergence of advanced language models such as BERT (Bidirectional Encoder Representations from Transformers) and GPT (Generative Pre-trained Transformers), which have been used for tasks like sentiment classification and aspect extraction, resulting in improved performance compared with traditional methods. For instance, Liu & Zhao [20] implemented a BERT model for aspect-level sentiment classification while Zhang et al. [21] fine-tuned a GPT model for aspect extraction, both achieving significant results.

Combining ABSA with Natural Language Inference (NLI) creates robust models that are capable of transferring knowledge across domains without the need for domain specific annotated data; whereby ABSA problems are rephrased into NLI problems where the hypothesis represents an opinion's associated polarity towards an identified aspect within review text whilst premises represent said text itself - this technique enhances zero shot transfer learning as well as few shot learning capabilities when applied to sentiment analysis, thus improving overall efficacy across various domains and applications alike. Additionally, it increases interpretability by providing explicit predictions between aspects present within reviews alongside associated opinions therein – ultimately facilitating decision making processes businesses may undertake more efficiently than before possible.

As an example, hotel reviews have had their sentiments analyzed using ABSA; specifically, through weighted multiple-instance learning approaches designed explicitly towards explaining star ratings given by customers [22].

## 3. Methodology

A large dataset of online reviews was collected from the TripAdvisor platform, comprising a total of 880,000 reviews for 1581 restaurants in the Algarve region, spanning from 2010 to 2023. To ensure validation, a stratified random sample (n=1000) was drawn from the complete dataset, based on the language of the reviews. The distribution of the reviews by language was as follows, in descending order: 55% English, 19% Portuguese, 8% French, 7% Spanish, 4% German, 4% Dutch, 2% Italian, 1% other.

To evaluate the proposed model's ability to extract the eleven mentioned attributes from the reviews and determine their sentiment (positive or negative), this sample of reviews underwent manual classification by three distinct human groups, designated as H1, H2, and H3. To assess the consistency and agreement among human classifications, each individual human classification was used as a reference point and compared to the others. The F1 Score values, which measure the accuracy of these comparisons are presented in Table 2.

Table 2. F1 Score between human attributes extraction.

<b>F1 SCORE</b>	<b>Human 1</b>	<b>Human 2</b>	<b>Human 3</b>
<b>Human 1</b>	1.0	0.83	0.91
<b>Human 2</b>	0.83	1.0	0.92
<b>Human 3</b>	0.91	0.92	1.0

Human classifications of the same review set are subjective and can vary, evidenced by an F1 Score between 0.86 and 0.92. Such findings are consistent with prior research as cited in [23]. The dataset with human classifications will be a benchmark for evaluating the automated classification methods presented.

This study introduces three distinct methods for extracting sub-attributes from restaurant reviews and determining their sentiment as either positive or negative. Each review is first pre-processed, involving the elimination of superfluous characters, transforming all text to lowercase, and segmenting the review into sentences based on delimiters like periods and exclamation points. Sentences must have a minimum of two words. The review's title, often summarizing the content, is then added to the review sentences.

The initial method applies a two-phase extraction and classification for each review sentence. The first phase employs a Natural Language Inference (NLI) Classifier with eleven labels to detect potential attributes from a predefined set. The second phase uses the NLI Classifier, now with two labels, to ascertain the sentiment of these attributes as positive or negative. This is depicted in Figure 1.

The subsequent method merges extraction and classification into one step. It still leverages an NLI Classifier but has enlarged and duplicated labels to cover both sentiments, totalling twenty-two labels. Here, the NLI Classifier extracts attributes and their sentiments concurrently, as shown in Figure 2.

Within the first two methods, two classifiers, BART and DeBERTa, are employed:

- The BART model (Bidirectional and Auto-Regressive Transformer) combines a bidirectional encoder (similar to BERT) with an autoregressive decoder (similar to GPT) into a single sequence-to-sequence model. The specific variant used, facebook/bart-large-mnli, is hosted on Hugging Face and contains over 407 million parameters (cross-encoder/nli-deberta-v3-large).
- The DeBERTa model (Decoding-enhanced BERT with Disentangled Attention) improves upon BERT and RoBERTa using two techniques: disentangled attention and an enhanced mask decoder. The specific variant used, microsoft/deberta-xlarge-mnli, is hosted on Hugging Face and contains over 750 million parameters (deberta-xlarge-mnli).

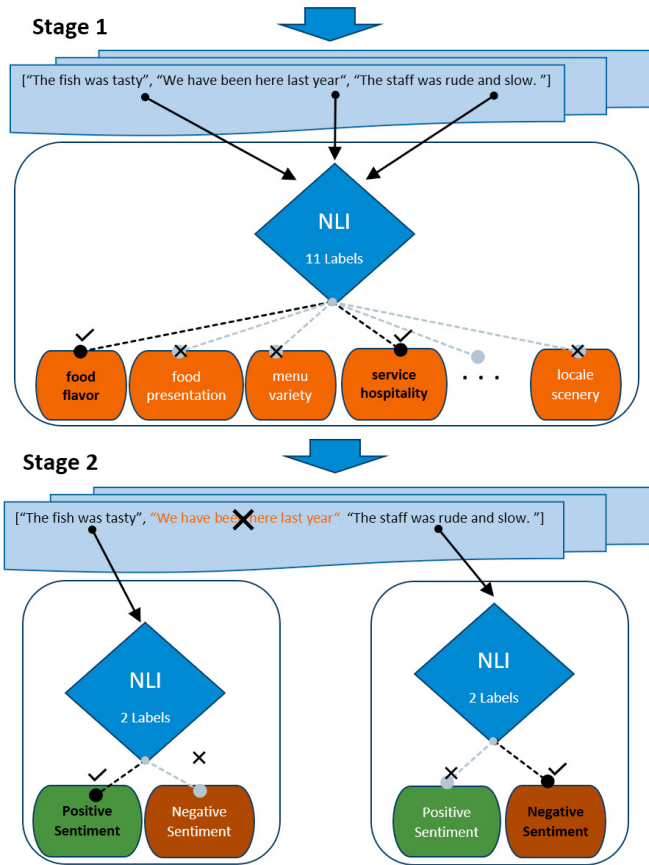


Fig. 1. Two stages NLI approach

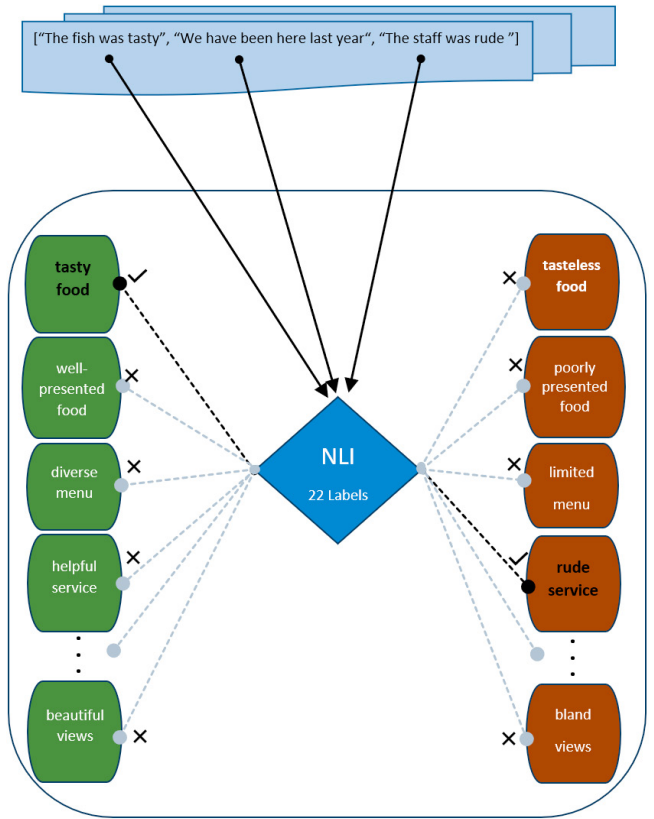


Fig. 2. One stage NLI approach

The third approach employs the Large Language Model (LLM) ChatGPT to discern the established eleven attributes and classify them within the entire online review. Specifically, versions 3.5 and 4.0 of ChatGPT, an AI dialogue system crafted by OpenAI, leverage the transformer framework to produce text resembling human responses based on given prompts. Available through OpenAI's API, this model is versatile in its applications, predicting subsequent words in sequences. It's believed to comprise over 175 billion parameters. To extract and categorize online reviews, a unique prompt was utilized, depicted in Figure 3.

```
prompt = ""
You are a helpful restaurant review analyst tasked with extracting and labeling sentiment (positive or negative) from the text of an online review. Your goal is to identify the sentiment for a set of attributes related to a restaurant experience, including 'food flavor', 'food presentation', 'menu variety', 'service hospitality', 'service efficiency', 'ambiance decoration', 'ambiance acoustics', 'ambiance cleanliness', 'price', 'locale accessibility', and 'locale scenery'.

Example:
Query:
review = "Great view of the beach. The pizzas looked and tasted good, but the staff were rude. The restaurant was chic but a bit noisy."
Response:
Food Taste (positive)
Food Presentation (positive)
Service Hospitality (negative)
Ambiance Decoration (positive)
Ambiance Acoustics (negative)
Locale Scenery (positive).

End of example.

CONSIDER ONLY ATTRIBUTES THAT ARE CLEARLY REFERRED IN TO THE REVIEW.

ONLY INCLUDE IN THR RESPONSE:
- THE POSITIVE AND NEGATIVE ATTRIBUTES
- EXCLUDE ALL ATTRIBUTES (NOT INDICATED) IN THE REVIEW.

""
```

Fig. 3. ChatGPT custom prompt

## 4. Results

To assess the extraction and classification capabilities of the proposed models, each approach was tested on a sample dataset of 1000 reviews and the results were compared with the reference human extraction and classification on eleven sub-attributes, as indicated in Table 3. The findings revealed that the BART model consistently outperformed the DeBERTa model across both 1-stage and 2-stage versions, with F1 scores of 0.73 and 0.66 for the former compared to 0.65 and 0.55 for the latter respectively. The threshold scores for labelling activation used for each of the Natural Language Inference (NLI) models were experimentally determined as  $s > 0.98$  for NLI (1 stage) and  $(s_{stage1} > 0.98, s_{stage2} > 0.55)$  for NLI (2 stages). Notably, ChatGPT 4.0 achieved a particularly high F1 Score of 0.77 in comparison to human performance on the same dataset which ranged from 0.83 to 0.92.

It is worth noting that BART (1 stage) model offers a practical solution which is available as open source at no cost, while ChatGPT can only be accessed through a commercial API incurring usage cost. In this context BART model seems more suitable as an effective way to automatically extract and classify attributes from large volumes of online reviews considering their complexity and subjectivity.

Table 3. Results.

Models	F1 Score	F1 Score (Macro)
bart-large-mnli (1 stage)*	0.73	0.82
bart-large-mnli (2 stages)**	0.65	0.79
deberta-xlarge-mnli (1 stage)*	0.66	0.78
deberta-xlarge-mnli (2 stages)**	0.55	0.73
ChatGPT3.5	0.75	0.84
ChatGPT4.0	0.77	0.88

\*( $s > 0.98$ )    \*\*( $s_{stage1} > 0.98, s_{stage2} > 0.55$ )

## 5. The RestMON Algarve web application

The RestMON Algarve web application, developed based on the set of attributes defined in section 2 and utilizing the BART (1 stage) model as described in previous sections, is a prototype monitoring platform that aims to provide detailed information to restaurant managers and potential customers located within the Algarve region. This application extracts and classifies approximately 880,000 online reviews from TripAdvisor between 2010–2023 for 1851 restaurants in this area. The extraction process captures 11 detailed attributes related to gastronomic experience which can be used by managers for making more informed decisions. Furthermore, it allows analysis of attribute evolution over time with options such as monthly/quarterly/yearly analysis or visual comparisons across specific aspects like geographical location or cuisine type among competing restaurants (as illustrated in Figure 4)

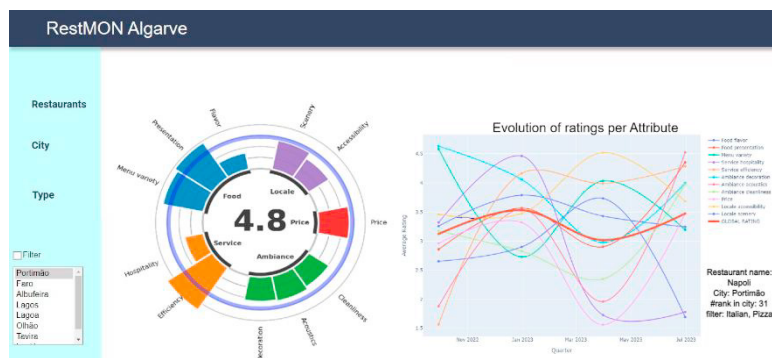


Fig. 4. RestMON Algarve interface

## 6. Conclusions and limitations

In essence, this study introduced a flexible, automated technique for extracting and evaluating customer sentiments in the restaurant sector through online reviews. Leveraging sophisticated Natural Language Processing (NLP) methods like Aspect-Based Sentiment Analysis (ABSA), the system enables precise categorization of customer feelings about specific attributes such as food quality, service, ambiance, cost, and location. The results indicate that our method effectively mirrors human sentiment analysis and categorization. The research offers three unique methods for attribute extraction and classification, highlighting the superior performance of the BART model over the DeBERTa model, with ChatGPT achieving the top F1 Score. This is crucial for hospitality managers. Adopting these recommended techniques and the related web application can provide managers with deeper insights into customer feedback on service attributes like food quality. Furthermore, by adopting these tools, leaders can monitor changes among competing establishments over time, aiding in more informed decision-making and optimizing customer satisfaction. However, a limitation is the study's reliance on a 1000-review sample dataset. Although promising, these results might not represent larger dataset's variability. The focus was also on the Algarve region's restaurant industry, potentially limiting wider applicability. Future research should involve bigger, diverse datasets to confirm this methodology's broader efficacy.

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