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Exploring Natural Language Processing and Sentence Embeddings for Sentiment Analysis of Online Restaurant Reviews

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Abstract

This paper explores the application of Natural Language Processing (NLP) methods in sentiment analysis of restaurant reviews available online, for a sample of restaurants in the Algarve region. The primary objective was to develop an automated method that could efficiently extract and categorize relevant sentiments relating to five key attributes of customer satisfaction, namely food quality, service, ambient, price and restaurant's location. Using the F1 Score the proposed method was compared against human classification benchmarks. The results showed that Universal Sentence Encoding (USE) was a suitable method for implementation due to its acceptable F1 score performance, ease of accessibility and reduced cost. The use of semantic embeddings can provide valuable insights from online reviews that could benefit the restaurant management and in general the data-driven decision-making processes businesses in the gastronomic sector.

Keywords: Natural Language Processing (NLP); Sentiment Analysis; Online Reviews; Gastronomic Sector; Sentence Embeddings.

1. Introduction

The gastronomic sector plays a crucial role the Algarve's economic and tourism landscape, a region known for its culinary variety and exceptional tourism quality (INE, 2022). It is well-established that dining serves as a principal attraction for individuals on holiday (Pizam et al., 2004). On a global scale, tourists are estimated to allocate one-quarter of their total expenditures on food and beverages (Wilkinson, 2016). Consequently, the effective management of restaurants is necessary to ensure both customer satisfaction and the commercial viability of the establishment (Namkung & Jang, 2008). Given the rising trend of tourists spreading their experiences on online review platforms such as TripAdvisor (Yoo et al., 2016) these platforms are emerging as an effective source of data, and subsequently attracting increased interest from the academic sector and also from the tourism sector (Xiang et al., 2017).

The act of employing semantic analysis through cutting-edge Natural Language Processing (NLP) methodologies allows for a nuanced understanding of online restaurant reviews. This provides crucial insights into various operational aspects, be it areas where the establishment excels or requires enhancement (Huang et al., 2014). These gleaned insights serve as pivotal informants for the formulation of more efficacious management strategies. Furthermore, advancements in word and

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sentence embedding technologies within the NLP domain have substantially elevated the capability to dissect and comprehend this form online data. Such progresses have led to transformative impacts across multiple sectors, including but not limited to, the hospitality industry. A salient application herein lies in the meticulous analysis of online customer reviews and recommendations specific to the restaurant sector.

Semantic embeddings, as an NLP technique - which capture complex meanings in high-dimensional vector spaces - can for example, provide an in-depth interpretation of human language as expressed in online reviews. These tools offer invaluable insights, ranging from customer sentiments about specific menu items to the overall dining experience. This distinct ability increases the performance of recommendation systems and serves as a strong tool for informed decision-making, leading, potentially, to more effective restaurant management strategies.

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 reviews related works on the topics of electronic word of mouth, the definition of the main attributes of a restaurant experience, and the use of embeddings in review analysis. Section 3 outlines the methodology used in this study. Section 4 presents the results obtained and, finally, Section 5 discuss the conclusions drawn from the study.

1.1. Research objectives

In the contemporary digital landscape, social media platforms function as relevant channels for users share their opinions and viewpoints, contributing to a rich generation of informative and valuable data. The primary objective of this study is to propose a flexible, automated methodology designed to extract complex and valuable information related to customer sentiment, whether positive or negative, for a set of key attributes relevant to the restaurant experience. These attributes include food, service, ambient, pricing, and location.

The proposed model is tested on a sample of multilingual restaurant reviews (n=1000) collected from the major recommendation platform in Portugal, TripAdvisor, specifically considering the Algarve region. The secondary aim of the study is to evaluate the feasibility of the proposed methodology by comparing its performance against a human classification of these attributes. The intent is to determine whether an automated approach can successfully and accurately replicate the human process in analyzing and classifying the complexities of customer sentiment in a set of defined attributes.

1.2. Contributions

The primary contribution of this study is an automatic model that makes use of sentence embeddings. This model offers a flexible method to classify an extensive collection of online reviews, whether they are related to restaurants, or eventually, other aspects of the hospitality sector. It categorizes reviews into custom groups of attributes or sub-attributes, identifying either positive or negative sentiments. Additionally, this model demonstrates potential regardless of the original language of the review. Furthermore, another significant contribution is the result from a comparative test. This test compares the classifications made by the proposed model with those made by human users. The results suggests that the model shows favorable potential based on the tested sample.

2. RELATED WORKS

2.1. eWOM – electronic Word of Mouth

In the current digital era, Electronic Word of Mouth (eWOM) constitutes a critical facet of consumer communication. It incorporates any form of consumer-to-consumer exchange or opinion diffusion via online platforms such as review sites, forums, and social media (Brown et al., 2007). Particularly within sectors like tourism, eWOM assumes an instrumental role, offering a mirror to customer attitudes, experiences, and intentions (Doosti et al., 2016).

In the context of hospitality, and particularly within the restaurant sector, the role of eWOM is accentuated due to various factors:

- Information Source: Current consumers, equipped with technological knowledge, regularly resort to online sources to conduct research before arriving at dining decisions. eWOM, facilitated through online reviews and ratings, supplies them with information about the food quality, service, and the comprehensive dining experience at a given restaurant.
- Trust and Credibility: Consumers are inclined to place more faith in the experiences and opinion of their peers compared to promotional content originating from the restaurant. This renders eWOM a highly credible information source that can significantly influence consumer decisions.
- Increased Visibility: eWOM contributes to enhancing the online visibility of a restaurant. When customers publish reviews or share their dining experiences online, it can amplify the restaurant's search engine ranking, thus facilitating its discovery by potential customers.
- Customer Feedback: eWOM acts as a valuable feedback mechanism for restaurants, enabling them to comprehend customer expectations, preferences, and areas requiring improvement. Engaging with online reviews can also underscore a restaurant's dedication to customer satisfaction.
- Impact on Sales: Positive eWOM can catalyze increased sales by attracting new customers and fostering repeat patronage. Conversely, negative eWOM can dissuade potential customers, underscoring the necessity for restaurants to assure a superior dining experience.

Given these considerations, it is imperative for restaurants to adopt a proactive perspective in managing eWOM. This could include encouraging content customers to broadcast their positive experiences online, addressing negative reviews in a constructive manner, and harnessing feedback to enhance service quality and customer satisfaction.

2.2. *Measuring a restaurant experience*

Customer satisfaction is intrinsically connected to positive customer behaviors and intentions, featuring the importance of discerning the attributes that support customer expectations and their correlation to favorable responses (Liu & Jang, 2009). Therefore, it is advantageous for restaurants to formulate strategies that strengthen their competitive advantages.

The link between perceived quality, customer satisfaction, and customer behaviors calls for an exploration of how attributes influence their satisfaction. These attributes are fundamentally connected to customer satisfaction and their subsequent reviews of restaurants. However, the delineation of these attributes presents a challenge due to disparate opinions among researchers regarding the quantity and type that should be factored into the evaluation of restaurant quality (Tiago et al., 2015).

A considerable number of studies have identified meal experience, food and beverages, service, ambient, price, and value as pivotal factors for consumer in the restaurant selection process (Silva, et al. 2009). While food quality is widely agreed upon as the dominant attribute, the importance of other factors should not be underestimated. Pantelidis (2010) suggests that, despite numerous studies, the primary factors remain ambiguous. However, in his model, the crucial attributes are food, service, ambient, price, menu, and decoration, listed in descending order of importance.

Pacheco (2018) isolates four specific attributes: food, service, cost-benefit ratio, and ambient, concluding that the first two ensure overall satisfaction. On TripAdvisor, food, service, and price are consistently visible attributes, while ambient is not always so.

Other researchers propose that the key attributes are food, service, and ambient, with Liu & Jang (2009) adding quality/price ratio and authenticity (for ethnic restaurants) to the mix. Each attribute, particularly food, can be further broken down into subcategories such as presentation, menu variety, healthy options, taste, freshness, temperature, and safety, each impacting customer satisfaction in distinct ways.

Service quality, a subjective measure, is contingent upon the discrepancy between expectations and perceived performance. The dining experience encompasses not just food quality but also service interactions. Jeong & Jang (2011) identified instances where service interactions superseded other factors as the primary attribute for customer satisfaction. Angnes & Moyano (2013) along with Mellinas & Reino (2018) introduce the location attribute into the list of considerations. Given the varied set of attributes presented in the literature, for the purposes of this study, the methodology described in the subsequent sections will be conducted with a set of five attributes: food, service, ambient, price, and location, as described in the next table.

ATRIBUTES	REFERENCES
1. Food	Tiago et al., 2015; Pacheco, 2018; Angnes & Moyano, 2013; Pantelidis, 2010; Silva, Medeiros & Costa, 2009.
2. Service	Tiago et al., 2015; Pantelidis, 2010; Pacheco, 2018; Silva et al., 2009.
3. Ambient	Tiago et al., 2015; Angnes & Moyano, 2013; Pantelidis, 2010.
4. Price	Tiago et al., 2015; Pantelidis, 2010; Silva et al., 2009.
5. Location	Angnes & Moyano, 2013; Mellinas & Reino, 2018.

Table 1 – Attributes of restaurant experience

2.3. Embedding Approach

Word embeddings and sentence embeddings are two fundamental bases in the field of Natural Language Processing (NLP). They are part of the broader family of distributed representations which capture semantic and syntactic meanings of words and sentences in a low-dimensional vector space (Bengio et al., 2003). These methods have revolutionized NLP, allowing for improved performance across a broad array of applications, ranging from sentiment analysis (Socher et al., 2013) to machine translation (Sutskever et al., 2014).

Word embedding is a technique where individual words of a language are represented as real-valued vectors in a predefined vector space. Each dimension in this space can correspond to a different feature that defines the word (Mikolov et al., 2013). This representation makes it possible for similar words to have similar embeddings, i.e., they are closer to each other in the vector space. Semantically related words are consequently expected to be in close proximity within this space.

Two of the most popular word embedding techniques are Word2Vec (Mikolov et al., 2013) and GloVe (Pennington et al., 2014). Both techniques learn embeddings by leveraging the context in which words appear. Word2Vec uses a shallow neural network to learn word associations from raw text, whereas GloVe constructs a global word-word co-occurrence matrix from the corpus and factorizes it to generate the embeddings.

While word embeddings provide a way to represent individual words, they fall short in capturing the meaning of longer text sequences like sentences. Sentence embedding techniques have emerged to fill this gap, aiming to encapsulate the semantic content of a sentence in a single vector.

A straightforward method to create sentence embeddings involves aggregating the embeddings of individual words within a sentence. However, this approach falls short in capturing the sequence and interaction of words. More advanced methods such as InferSent (Conneau et al., 2017) and

Universal Sentence Encoder (Cer et al., 2018) employ complex models like recurrent neural networks (RNNs) or transformers to encode the sequential data within sentences.

In this regard, recent embeddings models from OpenAI provide vectors of higher dimensionality as an outcome of the embedding process (Gomez et al., 2020). These vectors have 1,536 dimensions, a considerable increase compared to the typically used 512 dimensions in the Universal Sentence Encoder.

2.4. Embeddings for Review Analysis

The extensive amount of online restaurant reviews represents a valuable data collection for comprehending customer sentiments and preferences. Using word and sentence embeddings enables the extraction of high-quality features from these reviews, useful for predictive modeling or classification activities. Sentiment analysis or opinion mining, which determines if a review is positive, negative, or neutral, is a notorious application that has been improved using embeddings (Yu et al., 2017). Embeddings convert text data into numeric form, thus enabling the application of various machine learning techniques to the text of the reviews. This can yield significant insights, such as locating common themes in negative reviews, identifying trending dishes, or predicting future customer satisfaction levels based on review data (Tang et al., 2015).

In the tourism sector, Wen et al. (2023) used the BERT and ERNIE embedding models to analyze sentiments in online reviews. Particularly in the restaurant domain, Li et al. (2021) proposed a sentiment analysis model based on various embedding models (Word2vec, Bi-GRU, and Attention methods) that showed improved performance over traditionally used sentiment analysis models.

The abundance of online restaurant reviews constitutes a rich repository of data that is instrumental for understanding customer sentiment and preferences. Utilizing sophisticated embedding techniques, such as BERT (Bidirectional Encoder Representations from Transformers), USE (Universal Sentence Encoder), and OpenAI GPT models, can significantly enhance the quality of features extracted from these textual reviews, thereby amplifying the efficacy of predictive models or classification algorithms.

Sentiment analysis, also known as opinion mining, is a notable application that has undergone considerable improvement through the use of advanced embeddings. According to a study by Yu et al. (2017), embeddings facilitate the transformation of text data into a numerical format, thereby enabling the deployment of various machine learning methodologies on the review text. This numerical transformation yields actionable insights, such as identifying prevalent issues in negative reviews, pinpointing trending dishes, and prognosticating future customer satisfaction metrics (Tang et al., 2015).

In the realm of tourism, a recent study by Wen et al. (2023) employed BERT and ERNIE embedding techniques to scrutinize sentiments present in online reviews. Specifically focusing on the restaurant industry, Li et al. (2021) devised a sentiment analysis model that incorporated an array of embedding methodologies—including Word2vec, Bi-GRU (Bidirectional Gated Recurrent Units), and Attention mechanisms. This model exhibited a marked improvement in performance compared to traditional sentiment analysis models.

In this paper, for the purpose of online review classification, three prominent embedding models—BERT, USE, and OpenAI GPT—are employed. The principal characteristics of each of these models are described next to provide a comprehensive understanding of their unique capabilities and applications.

The BERT model (Bidirectional Encoder Representations from Transformers) developed by Google in 2018, is distinguished for its capability to understand context bidirectionally, thereby capturing the semantic nuances of each word in a sentence through its surrounding lexical elements. This unique feature renders BERT highly effective for tasks that demand a nuanced understanding of context, such as sentiment analysis in online reviews.

The USE model (Universal Sentence Encoder) also created by Google in 2018, specializes in generating fixed-length sentence embeddings with a strong focus on encapsulating the semantic core of sentences. The fixed-length nature of these embeddings, coupled with their semantic richness, makes USE particularly adept at clustering reviews and computing semantic similarities, thereby facilitating effective online review classification.

Finally, the OpenAI GPT Models (Generative Pre-trained Transformers) released in 2022 by OpenAI's research are primarily designed as unidirectional models with a core competency in text generation. Despite this, they possess the flexibility to be fine-tuned for a range of tasks, including sentiment analysis. One of their standout features is their ability to generate text that is both coherent and closely mimics human language patterns.

3. METHODOLOGY

From the attributes of a restaurant experience defined in section 2 (food, service, ambient, price, and location), a large corpus of reviews was collected from the platform TripAdvisor. The scope of the collection focused on restaurants in the Algarve Region (south of Portugal). In total, 28,427 reviews were extracted from 711 restaurants (using the criteria of 100 or more reviews in the past 2 years). To ensure the representativeness of language distribution in the subsequent analysis, a stratified random sample of 1,000 reviews was extracted from this large dataset. This sampling strategy was designed to mirror the language composition of the original corpus. Consequently, the language distribution within the sample aligned closely with the original dataset and was categorized as follows, in descending order: 55% in English, 19% in Portuguese, 8% in French, 7% in Spanish, 4% in German, 4% in Dutch, 2% in Italian, and 1% in other languages.

To evaluate the capability of the proposed model to extract the five mentioned attributes from the reviews and determine their sentiment (positive or negative), this sample of reviews was then subjected to manual classification by three distinct human groups, labeled as H1, H2, and H3.

To assess the coherence and regularity of the classifications, each individual human classification was used as a reference point and subsequently compared to the others. The F1 Score values, which measure the accuracy of these comparisons, were calculated, and are shown in Table 2.

F1 SCORE	**H1**	**H2**	**H3**
H1	1.0	0.93	0.91
H2	0.93	1.0	0.86
H3	0.91	0.86	1.0

Table 2 – F1 Score between human attributes extraction.

As can be observed, the coherence of human classifications for the same set of reviews is variable and subjective, with the F1 Score ranging from 0.86 to 0.93. Indeed, this evidence aligns with findings from literature studies (Wang, 2022).

To operationalize the automatic approach for extracting the defined attributes and their respective sentiment, the proposed methodological approach is generically represented in Figure 1.

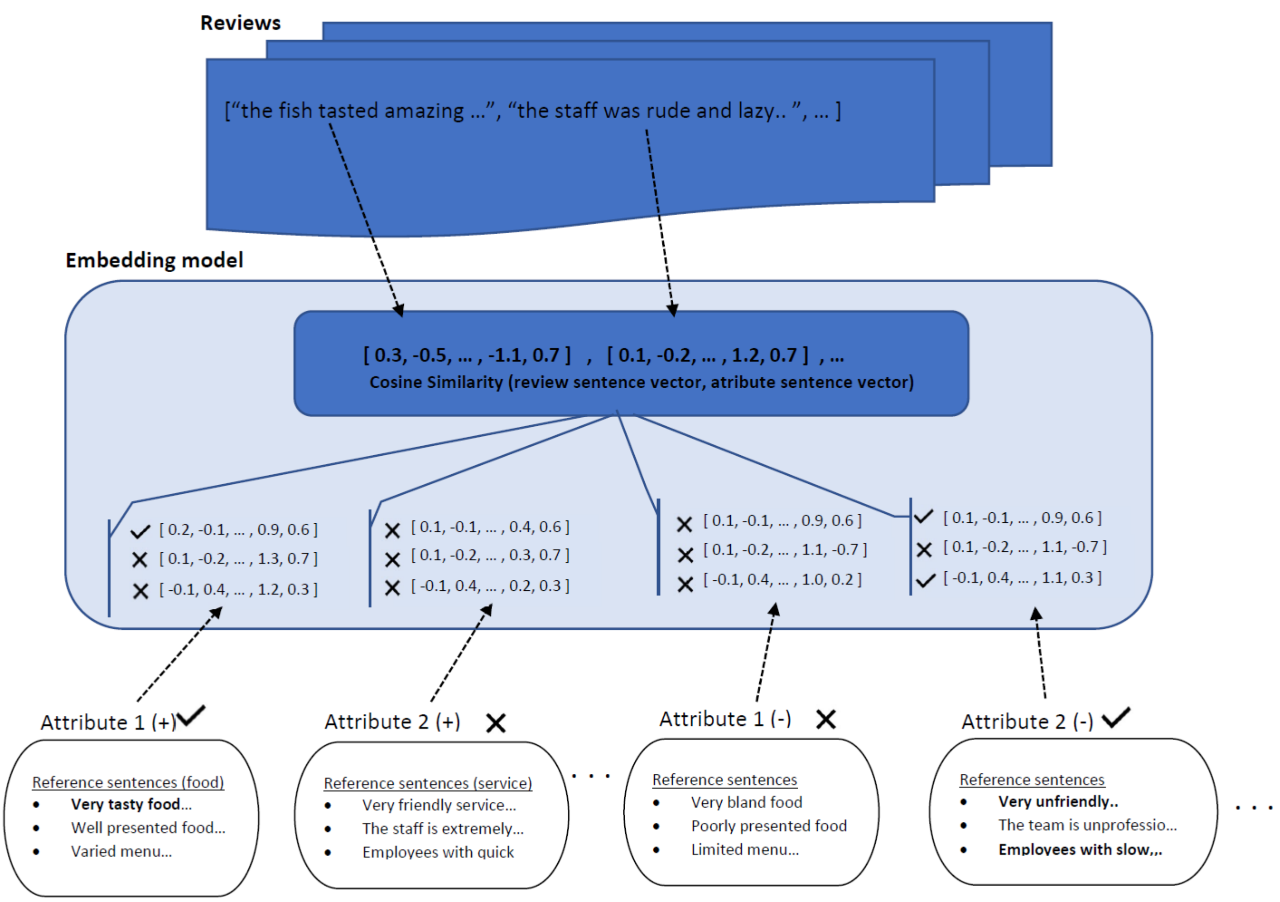

Figure 1 – Outline of the semantic analysis embedding approach.

In the initial stage, each of the reviews go through a preprocessing procedure. During this phase, redundant characters (such as spaces or repeated symbols) are eliminated. All text is converted to lowercase. The complete review text is divided into sentences using separation characters (periods, exclamation points, newlines, and new paragraphs). In addition, each sentence must contain at least two words. Finally, the text corresponding to the review title (which is typically shorter) is concatenated to the review sentences, as it usually provides a relevant summary of the review.

As a reference for each of the considered attributes, three reference sentences were created exploring those attributes, which will serve to measure similarity with each sentence of every review (table 3).

	ATRIBUTES	REFERENCE SENTENCES
Positive	1. Food (+)	"Very tasty food. Fantastic and delicious flavor. Good meal." "Well presented food. Well served dish. Excellent presentation." "Varied menu. Good variety of dishes and drinks. Many wine options"
	2. Service (+)	"Very friendly service. Kindness and professionalism", "The staff is extremely professional, polite and attentive. Fantastic staff.", "Employees with quick and efficient service.",
	3. Ambient (+)	"The atmosphere is charming. Relaxing ambient.", "The decor is sophisticated, stylish, modern and elegant, with soft lighting and pleasant background music. The space is large and comfortable", "The restaurant was very clean, and the WC was hygienic.",
	4. Price (+)	"Excellent value for money. Fair price. Affordable price.", "Great cost-benefit ratio. Economical. Cheap", "Very reasonable prices. Fair prices",
	5. Location (+)	"The location is good and has a fabulous view.", "The location is accessible, and the parking is easy and close.", "The views are panoramic and wonderful.",
Negative	1. Food (-)	"Very bland food. Unpleasant and poor-quality flavor. Terrible food.", "Poorly presented food. Poorly served dish. Terrible presentation.", "Limited menu. Little variety of dishes and drinks. Few options of dishes and wines.",
	2. Service (-)	"Very unfriendly and terrible service. Lack of kindness and professionalism.", "The team is unprofessional, rude and inattentive.", "Employees with slow and inefficient service.",
	3. Ambient (-)	"The atmosphere is unpleasant. Noisy ambient.", "The decor is outdated, old-fashioned and simplistic, with strong lighting and unpleasant background music. The space is cramped and uncomfortable.", "The restaurant was dirty, and the WC was unhygienic.",
	4. Price (-)	"Terrible value for money. Exorbitant price. Unaffordable price", "Bad cost-benefit ratio. Expensive. Extremely high price by comparison", "Very high prices. Bad prices",
	5. Location (-)	"The location is horrible and has a terrible view", "The location is difficult, and the parking is limited and far away.", "The views are obstructed and unpleasant."

Table 3 – References sentences for each attribute (positive and negative)

The reference sentences are divided into two groups (positive and negative) to improve their comparison with the reviews, enabling the extraction of sentences with opposite sentiments within the same review. Thus, each of the initial reviews will be translated into a set of ten binary values, identifying if any of the five attributes were mentioned in a positive or negative manner within that full review. The procedure for comparing and classifying each sentence of the review and the various attributes considered is performed through semantic analysis. For this purpose, the vector embeddings of each review sentence are compared to each of embeddings of the reference sentences, using the cosine similarity metric.

$$cosine\ similarity\ (S_{rev}, S_{ref}) = \frac{S_{rev} \cdot S_{ref}}{\|S_{rev}\| \|S_{ref}\|}$$

Where S_{rev} and S_{ref} are the embeddings vectors of the review sentence and reference sentence, respectively. For each review sentence, the attribute is classified according to the reference sentence that has the maximum cosine similarity, along with the sentiment (positive or negative). Furthermore, a minimum threshold value (≥ 0.3) for cosine similarity was set experimentally to prevent the detection of irrelevant attributes.

This methodology is based in semantic analysis, which, in this case, relies intrinsically on the chosen embedding model. Therefore, to assess the applicability of this approach, three alternative sentence embedding models were evaluated:

- **BERT -** Language-agnostic sentence embedding model, 109 languages, (768 dimensions)
- **USE -** Universal Sentence Encoding - multilingual, sixteen languages, (512 dimensions)
- **OpenAI -** Embeddings (Ada-002) – multilingual, (1,536 dimensions)

4. RESULTS

Each sentence embedding model was employed to identify attributes within the stratified random sample of 1,000 reviews. Subsequently, the automated classifications generated by these models were compared against pre-existing human classifications, which were previously denoted as H1, H2, and H3. In the proceeding tables, these human classifications are categorized under the label HUMAN EXTRACTED. For the purposes of this study, these human-derived classifications function as the definitive and true labels. In total, each embedding model generated 10,000 predictions—five positive and five negatives for each review. The distributions of these predictions are delineated in the tables that follow.

MODEL (BERT) (F1 Score = 0.79)		MODEL PREDICTED	
		0	**1**
HUMAN EXTRACTED	**0**	7395	405
	1	502	1698
(Accuracy = 0.91, Precision = 0.81, Recall= 0.77)			

Table 4 – Confusion matrix for model BERT

MODEL (USE) (F1 Score = 0.81)		MODEL PREDICTED	
		0	**1**
HUMAN EXTRACTED	**0**	7420	380
	1	460	1740
(Accuracy = 0.92, Precision = 0.82, Recall= 0.79)			

Table 5 – Confusion matrix for model USE

MODEL (OpenAI) (F1 Score = 0.85)		MODEL PREDICTED	
		0	**1**
HUMAN EXTRACTED	**0**	7492	308
	1	365	1835
(Accuracy = 0.93, Precision = 0.86, Recall= 0.83)			

Table 6– Confusion matrix for model OpenAI

As observed, the class distribution is significantly unbalanced, thereby necessitating the use of the F1 score as a more relevant metric to assess the performance of the embedding models. The F1 score is selected as the primary evaluation metric due to its ability to balance both precision and recall effectively. This balanced measure is of particular importance in the domain of sentiment analysis, where the ramifications of both false positives and false negatives are significant. In all of the tested models, the F1 Score is acceptable within the context of review classification, ranging from 0.79 for the BERT model to 0.85 for the OpenAI model. The latter only records an F1 score value marginally lower than the lower limit of the previous human classification comparison.

Regarding the comparability between embedding models and considering other key factors related to the model implementation, it is relevant to mention that both the BERT and USE models are freely accessible and can be implemented and executed locally without any costs. On the other hand, the OpenAI embedding model is provided in a remote access regime via commercial API, with usage costs. In this context, the USE (Universal Sentence Encoding) embedding model seems more suitable for an implementation that needs to automatically process a large volume of online reviews.

5. CONCLUSIONS

With dining being a significant attraction for tourists and online reviews forming a substantial part of decision-making, an automated model for the semantic analysis of these reviews can offer valuable insights. This study aimed to present an automatic methodology, employing NLP techniques, using embedding models, to extract and classify sentiments concerning essential restaurant attributes from a vast corpus of online reviews.

The attributes identified for analysis were food, service, ambient, price, and location. Each of these attributes are known to have considerable impact on customer satisfaction. To assess the feasibility and performance of the proposed model, it was compared against manual classification by three separate human groups. The model shown an acceptable F1 score within the context of review classification, which indicates a promising outcome for the proposed methodology.

Among the sentence embeddings models evaluated, the OpenAI model yielded the highest F1 score but was accessed via API, implicating usage costs. In contrast, the BERT and USE models are freely accessible and can be implemented locally. Considering these factors, the USE model is a feasible choice for applications necessitating the automatic processing of a large volume of online reviews. In conclusion, the paper demonstrated the potential for semantic embeddings in providing in-depth insights about customer sentiments in online reviews. As this automated methodology was able to replicate the human process of analyzing and classifying sentiments with reasonable accuracy, it can significantly benefit the gastronomic sector, as a source of valuable data for better and more informed decision-making in a restaurant management context. In future work, the scope of analysis will be expanded to incorporate additional and larger datasets with human labelling. Moreover, the potential application of other NLP techniques, such as NLP inference classifiers and Large Language Models (LLMs) with custom prompts classifiers, will be also investigated.

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