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Social Media Monitoring Of Airbnb Reviews Using AI: A Sentiment Analysis Approach For Immigrant Perspectives In The UK

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Abstract

This paper presents a novel approach for monitoring social media content related to Airbnb reviews, explicitly focusing on the sentiments expressed by immigrants in the United Kingdom. The proposed system, a Quick Search System, leverages machine learning techniques to perform sentiment analysis on many Airbnb reviews. The system aims to provide timely and insightful information about the experiences and sentiments of immigrants in the UK, as reflected in their Airbnb reviews. By employing state-of-the-art machine learning algorithms, the system enables efficient and accurate sentiment classification, allowing for the identification of key themes and sentiments expressed by immigrant users. The study demonstrates the potential of this approach in gaining a deeper understanding of immigrant perspectives within the context of peer-to-peer accommodation, and its implications for social media monitoring and customer satisfaction management.This present study has conducted a critical analysis utilizing efficient feature extraction techniques, including N-grams and TF-IDF, to optimize identifying positive, neutral, and negative feedback. Furthermore, five different models were utilized, and the training and testing processes were accompanied by parameter tuning. Ultimately, the study concluded that the Random Forest (RF) classifier performed exceptionally well, achieving a 95% accuracy rate.

Keywords: *Quick Search System, Sentiment Analysis, Machine Learning, n-grams, TF-IDF, Random Forest.*

A. Introduction

In recent years, the sharing economy has significantly transformed how people travel and seek accommodation. Platforms like Airbnbhave gained immense popularity, offering travellers a wide range of lodging options (O[1]skam, 2016). As a result, the impact of these platforms on various stakeholders, including immigrants, has become a subject of interest for researchers and industry professionals (Kas, 2022). This study focuses on the sentiment analysis of Airbnb reviews from the perspective of immigrants in the United Kingdom. By leveraging social media monitoring and sentiment analysis techniques, this research aims to gain insights into the experiences and perceptions of immigrants regarding their stays in Airbnb accommodations. The findings of this study are expected to provide valuable

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implications for both the immigrant community and the hospitality industry, shedding light on the nuances of their interactions within the context of the sharing economy.

B. Literature Review

The rise of social media platforms has transformed the way people communicate, allowing them to share their opinions, experiences and feelings about various services and products. In recent times, the hospitality industry - particularly platforms like Airbnb - has experienced a surge in user-generated content, including reviews and conversations on social media. This literature review examines the use of sentiment analysis techniques driven by artificial intelligence (AI) to monitor Airbnb reviews, with a particular focus on the perspectives of immigrants residing in the United Kingdom (UK).

Sentiment analysis, which is also referred to as opinion mining, is a computational technique that aims to extract and analyze sentiments, opinions, and attitudes expressed in textual data (Pang & Lee, 2008). This technique is particularly useful for businesses in the context of social media monitoring, as it enables them to gain valuable insights from user-generated content, such as reviews, comments, and posts. By understanding customer sentiments and preferences, businesses can improve their products or services and enhance their overall customer experience (Liu, 2012)& (Gandhi, 2021).

In addition to this, the hospitality industry has increasingly adopted sentiment analysis techniques to analyze customer feedback, manage brand reputation, and assess service quality (Li et al., 2019). Studies have explored sentiment analysis applications in various hospitality sectors, including hotels, restaurants, and vacation rentals, highlighting its efficacy in identifying trends, addressing customer concerns, and enhancing guest experiences (Xiang et al., 2015).

Furthermore, Immigrants represent a significant demographic within the UK hospitality sector, influencing workforce dynamics and consumer behaviours (Song et al., 2018). Immigrant perspectives on accommodation services, including those provided by platforms like Airbnb, are shaped by cultural backgrounds, language proficiency, and socio-economic factors (Brouder & Teixeira, 2012). Understanding immigrant experiences is crucial for hospitality businesses to tailor services and address cultural sensitivities effectively.

Despite the growing interest in sentiment analysis within the hospitality industry, limited research has focused explicitly on analyzing immigrant perspectives regarding Airbnb accommodations in the UK. The application of sentiment analysis techniques to immigrant-generated content on social media platforms presents an opportunity to gain insights into their experiences, satisfaction levels, and preferences (Bohme & Ziebarth, 2018).

Conducting sentiment analysis on immigrant perspectives poses challenges related to language diversity, cultural nuances, and sentiment ambiguity (Al-Samarraie&Eldenfria, 2018). However, advancements in natural language processing (NLP) and machine learning algorithms offer opportunities for developing accurate sentiment analysis models tailored to immigrant voices in the UK hospitality sector (Chen & Skoric, 2017). Leveraging AI-driven sentiment analysis tools enables real-time monitoring and proactive management of guest experiences on Airbnb (Mohammad & Bravo-Marquez, 2017). In conclusion, social media monitoring of Airbnb reviews using AI-driven sentiment analysis offers a promising approach to understanding immigrant perspectives in the UK hospitality sector. By analyzing sentiment patterns and identifying key themes in immigrant-generated content, hospitality businesses can enhance service quality, address cultural sensitivities, and foster positive guest experiences. Further research and empirical studies are warranted to explore the effectiveness of sentiment analysis techniques in capturing and interpreting immigrant sentiments within the context of Airbnb accommodations in the UK.

C. Methodology

In this study, we used the Airbnb dataset sourced from the Kaggle dataset to analyze the positive, neutral, and negative words from the customer text feedback. Initially, we processed the null values and missing values in the dataset to get the refined dataset, which gave the optimized solution for this data analysis process. The text processing techniques were handled to facilitate the automated analysis and organization of unstructured text data, thereby enabling ML models to discern and interpret human language effectively. Essentially, text processing is a fundamental tool for managing the extensive volumes of unstructured text data resulting from customer interactions with brands, enabling companies to glean valuable business insights. Consequently, text processing is pivotal across a spectrum of real-world applications spanning business and consumer domains, including chatbots, cybersecurity, search engines, big data analytics, talent acquisition, and streamlining routine legal tasks.

In this study, five text-processing methods were employed Tokenization, Punctuation removal, Stop word removal, Removing HTML Tags, and Lower casing (Chai, 2023). Considering this tokenization, the n-grams technique has been used to extract the words by single words as unigram, two words as bigram and three words as trigram. N-grams are advantageous due to their ease of computation and storage, rendering them suitable for large-scale tasks within natural language processing. Incorporating N-grams as features in machine learning models enables the capture of linguistic patterns, enhancing the models' capabilities in tasks such as text classification, sentiment analysis, and information retrieval.

Vectorization:

Vectorization, in technical terms, is the process of converting textual data into numerical vectors for computational analysis (Wendland, 2021). Natural language processing involves representing words, phrases, or documents as numerical values in a high-dimensional space. Techniques like TF-IDF and word embeddings are commonly used for vectorization, facilitating the application of machine learning algorithms to process and understand textual information. Vectorization is a fundamental step in NLP, enabling the transformation of textual data into a format suitable for mathematical operations and computational analysis.

N-grams

N-grams are contiguous sequences of N items within a given text, typically words (Sidorov, 2014). In natural language processing, N-grams are used to capture the contextual relationships between words. Bigrams represent pairs of consecutive words, while trigrams denote triplets, and so on. N-grams provide insights into the structure and nuances of language, offering a way to analyse patterns and relationships between adjacent words in a text. They are commonly employed in tasks such as text analysis, language modelling, and feature extraction for machine learning applications, enhancing the understanding of contextual information within a given textual dataset.

TF-IDF

TF-IDF (Term Frequency-Inverse Document Frequency) was utilized as a feature extraction technique for transforming text data into a numerical format suitable for machine learning models. The TF-IDF Vectorizer from the scikit-learn library was employed, allowing the conversion of bigrams and trigrams generated from the tokenized text into TF-IDF representations. This involved assigning numerical weights to each term based on its frequency within individual comments (TF) and its rarity across the entire dataset (IDF). The resulting TF-IDF matrices for bigrams and trigrams served as input features for various machine learning models, enabling them to understand and analyse the nuanced patterns within the text data for sentiment analysis.

Data Analysis

In the data analysis phase, a comprehensive approach was taken to extract meaningful insights from the text data. The initial step involved tokenization, breaking down the text into individual words, and subsequently applying lemmatization to reduce words to their base or root form, ensuring a more unified representation. Common stop words were then removed, emphasizing the importance of significant terms. Bigrams and trigrams were generated to capture nuanced contextual information, unveiling relationships between consecutive words. This pre-processed text underwent a thorough analysis, leveraging lemmatization to maintain semantic integrity. The resulting refined dataset provided a foundation for more in-depth exploration, revealing intricate patterns and subtle nuances contributing to a profound understanding of sentiment within the text.

Text processing

Several key steps were meticulously applied to refine and prepare the text data for analysis. The process began by uniformly converting the text to lowercase, ensuring consistency, and mitigating potential discrepancies stemming from varied cases. Punctuation marks, including commas, periods, and exclamation points, were systematically removed to streamline the focus on essential words and reduce the influence of non-essential characters.Following this, lemmatization was implemented, whereby words were transformed into their base or root forms, fostering semantic consistency and ensuring that variations of words shared a common representation. This step aimed to capture the underlying meaning more effectively. Subsequently, common stop words were eliminated to accentuate significant terms while still preserving the contextual intricacies of the text.

Moreover, numeric and alphanumeric characters were excluded, such as numbers and combinations of letters and numbers. This particular step focused the analysis on the textual content, eliminating potentially distracting numerical information. Finally, the generation of bigrams and trigrams provided valuable insights into relationships between adjacent words, capturing subtle nuances in language and enriching the dataset.This meticulous preprocessing encompassed a range of text processing steps, including lowercasing, punctuation removal, lemmatization, stop word removal, and numeric/alphanumeric exclusion. The cumulative effect of these measures not only streamlined the dataset but also maintained its richness, establishing a robust foundation for a profound and nuanced analysis of sentiment and language patterns within the text.

Feature Extraction

A thorough process was employed in the feature extraction phase to distil relevant information from the pre-processed text data. The initial step involved the creation of n-grams, specifically bigrams and trigrams, to capture meaningful sequences of words and unveil nuanced contextual relationships. These n-grams serve as features, providing a more comprehensive representation of the language patterns within the text (Nixon, 2019). Simultaneously, implementing lemmatization ensured a unified and semantically consistent feature set, reducing variations to their base forms. The subsequent application of feature extraction techniques, excluding TF-IDF as specified, aimed to highlight the importance of individual terms within the dataset. This meticulous feature extraction process not only refined the representation of the text but also enhanced the ability of machine learning models to discern patterns and make informed predictions based on the intrinsic characteristics of the language used.

N-GRAMS	CLASSIFICATION ACCURACY
UNIGRAM	72%
BIGRAM	81%
TRIGRAM	84%

Table 1: Performance of N-gram Features

We utilized efficient features and an intelligent system for the optimized search for the review feedback based on the n-grams and TF-IDF vectorization techniques.We used the machine learning approach to analyze the positive, neutral, and negative (High, Medium, and Low respectively) words from the customer text feedback. We can conclude that trigrams exhibit the highest performance on our training data.

Model training and testing

In the model training and testing phase, the focus is on imparting sentiment analysis capabilities to the computer through machine learning algorithms. This process can be likened to instructing a virtual assistant to categorize comments or reviews into positive, negative, or neutral sentiments (Gholamy, 2018).

Model Training

During the training phase, the computer assimilates knowledge from labelled examples. A set of comments, each labelled with sentiment (positive, negative, or neutral), serves as the training data. Models such as Decision Tree, Naive Bayes, Logistic Regression, and SVM (Rebecca J v, 2016) systematically analyse these examples, identifying intricate patterns and correlations between words and sentiments.

Model Testing

Following training, the models undergo testing using a separate set of comments not encountered during the training phase. This testing scenario simulates the model's performance in predicting new, unseen data sentiments. It assesses the generalisation capability of the models (Tian, 2018).The training and testing phase involves instilling sentiment analysis proficiency in the computer and evaluating its application on new data. Decision Tree, Naive Bayes, Logistic Regression, and SVM are selected as versatile models capable of capturing diverse text patterns.The model testing process is a critical phase in the development of any machine learning or statistical model. It involves evaluating the performance and accuracy of the model using independent datasets or through cross-validation techniques. During testing, the model's predictive capabilities are assessed against unseen data to determine its robustness and generalization ability. Various metrics, such as accuracy, precision, recall and F1-score are commonly used to quantify the model's performance.

Evaluation Metrics

Various metrics are employed to assess their performance quantitatively in evaluating sentiment analysis models (Zhou, 2021). Accuracy measures the overall correctness of predictions, representing the ratio of correctly predicted instances to the total. Precision focuses on the model's ability to accurately identify instances of a specific sentiment class, highlighting the avoidance of false positives. Recall, also known as sensitivity, gauges the model's capacity to capture all instances of a particular sentiment, especially crucial in scenarios where missing positive or negative sentiments carry significance. F1-score provides a balanced assessment by combining precision and recall, offering a harmonized measure of a model's effectiveness.

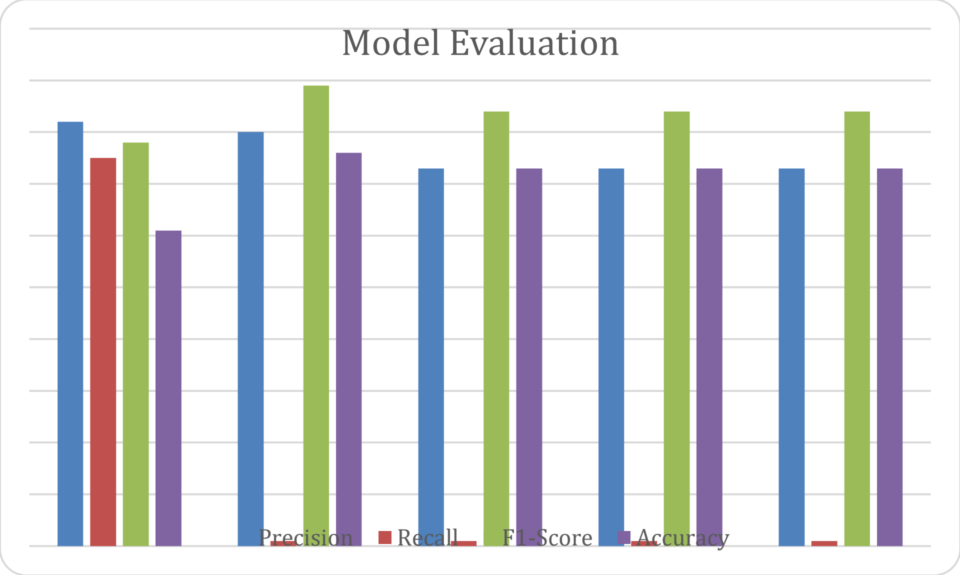

Figure 1: Different Model Evaluation and Analysis

Collectively, these metrics in Figure 1contribute to a nuanced understanding of a sentiment analysis model's strengths and limitations, guiding the selection and optimization of models based on specific task requirements and priorities.

D. Results and Discussion

From the results in Table 2, we can see that Random Forest has the highest precision, recall, F1-score, and accuracy among the classifiers evaluated, indicating that it performs the best on the given task. Naïve Bayes also shows respectable performance, although it has slightly lower precision, recall, and F1-score compared to Random Forest. Logistic Regression and SVM seem to have relatively low recall, indicating that they are not able to identify many of the positive instances in the dataset.

SNo	Classifiers	Precision	Recall	F1-Score	Accuracy (%)
1	Decision tree	85	87	84	87
2	**Random forest**	**96**	**95**	**95**	**95**
3	Naïve Bayes	72	85	78	85
4	Logistic regression	73	1	84	73
5	SVM	73	1	84	73

Table 2: Overall Analysis of the Different Classifiers

Confusion matrix

A confusion matrix typically represents the counts of true positive (TP), false positive (FP), true negative (TN), and false negative (FN) predictions (Rebecca J V, 2016). However, it seems the provided data might already represent these counts shown in Table 3.

	Pred Negative	Pred Neutral	Pred Positive
Negative	100	0	44
Neutral	0	54	24
Positive	0	0	1250

Table3: Confusion Matrix for Random Forest classifier

In this matrix:

- 100 instances of Negative sentiment were correctly classified as Negative (True Negatives).
- 54 instances of Neutral sentiment were correctly classified as Neutral (True Positives).
- 1250 instances of Positive sentiment were correctly classified as Positive (True Positives).
- 44 instances of Negative sentiment were falsely classified as Positive (False Positives).
- 24 instances of Neutral sentiment were falsely classified as Positive (False Positives).
- There are no False Negatives indicated in the provided data.

C. Conclusion

In conclusion, sentiment analysis, empowered by machine learning (ML) and artificial intelligence (AI), has emerged as a powerful tool with wide-ranging applications. By automatically identifying and categorizing opinions expressed in text data, sentiment analysis enables businesses to gain valuable insights into customer feedback, market trends, and brand perception. ML and AI techniques have significantly enhanced the accuracy and efficiency of sentiment analysis, allowing for the processing of large volumes of unstructured data in real-time. As the demand for understanding and leveraging customer sentiment continues to grow, integrating ML and AI in sentiment analysis will play a pivotal role in driving informed decision-making, improving customer experience, and shaping various industries. Therefore, sentiment analysis using ML and AI stands as a testament to the transformative potential of these technologies in understanding and harnessing the power of human language for meaningful business outcomes.In conclusion, the Random Forest model showcased exceptional predictive capabilities with a commendable accuracy of 95%. This highlights the efficacy of ensemble learning techniques in handling complex datasets and making accurate predictions. Overall, the findings underscore the significance of Random Forest and similar ensemble approaches in addressing classification tasks effectively.

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