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BIG DATA-BASED SENTIMENT ANALYSIS ON TRIPADVISOR REVIEWS USING NAÏVE BAYES CLASSIFICATION: A CASE STUDY ON LUXURY RESORT IN BALI

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ABSTRACT

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This research aims to analyze the sentiment of tourist reviews on the TripAdvisor platform towards a luxury resort in Bali by utilizing the Naïve Bayes classification method. The review data is analyzed to identify positive, negative, and neutral sentiments. Three variants of Naïve Bayes algorithm (GaussianNB, MultinomialNB, and BernoulliNB) were implemented and evaluated for performance. The results showed that the GaussianNB model provided the highest classification accuracy of 0.89. Further analysis revealed that the model effectively identified positive sentiments, but had challenges in classifying negative and neutral sentiments. Word cloud visualization confirmed the focus of positive reviews on aspects of accommodation, service and facilities, which can serve as a reference for the hospitality industry. This study concludes that big data-based sentiment analysis is an important tool for understanding customer perceptions, noting the need for further model development to improve the identification of minority sentiments.

Keywords: Sentiment Analysis; Big Data; TripAdvisor; Naïve Bayes; Luxury Resort, Bali

INTRODUCTION

The world is currently undergoing rapid changes, especially in the landscape of online communication and interaction, which significantly affects various aspects of life, including the way consumers share and access information (Agarwal, 2024). This digital era is characterized by a flood of data generated from various social media platforms, including popular travel review sites such as TripAdvisor (Baskoro et al., 2021). Online reviews have become an invaluable source of information for consumers, allowing them to understand other travelers' perceptions and experiences regarding product and service quality before making a decision (Thung et al., 2021). This provides an opportunity for potential consumers to learn about product quality and service satisfaction from the experiences of previous consumers without having to experience it themselves (Nadeak et al., 2023). This development has a significant influence on the hospitality industry, where understanding guest satisfaction is key to improving service quality and maintaining competitiveness (K.P et al., 2023). In the context of tourism, *online* reviews play an important role in shaping travelers' perceptions and decisions (Ciptasari et al., 2024; Sugiarta et al., 2024). This research contributes to the understanding of how sentiments expressed in *online* reviews can be analyzed to gain insights into digital consumer behavior in the hospitality industry.

As a luxury hotel, Bvlgari Resort Bali is one of the five-star accommodations that places guest satisfaction as a top priority. The tourism industry, especially the hospitality sector in Bali, has shown significant growth in recent years (PRATIWI, 2024). This is reflected in the increasing number of star hotels, including luxury hotels, operating in Bali so that hotels must be able to implement strategic planning and utilize it in order to win the competition (Teguh et al., 2020). The increasing number of businesses in the hospitality sector, especially accommodation, results in higher business competition among hotels in selling their products and services (Harefa et al., 2022). In this intense competition, the level of guest satisfaction is not only a business goal, but also an important indicator of the success of a hotel (Rahayu, 2023). Sentiment analysis can be a valuable tool in service quality management by providing direct feedback from customers on strong and weak aspects of service (Pitanatri et al., 2024, 2025). This research provides a methodology to automatically measure and analyze customer satisfaction from online reviews, which can support continuous service quality improvement efforts.

Increasingly fierce competition requires companies, including Bvlgari Resort Bali, to be able to provide high-quality services that meet the needs and desires of guests in order to compete and grow. As a luxury resort it also faces the challenge of maintaining guest satisfaction levels, which can fluctuate from time to time. These fluctuations in guest satisfaction levels can affect return visit rates and overall image (Jayanti & Yulianthini, 2022).

Through the reviews page on TripAdvisor, Bvlgari Resort Bali has the opportunity to gain valuable insights into its customer satisfaction levels. TripAdvisor, as one of the largest travel review platforms in the world, provides a large amount of data in the form of guest opinions and experiences (Seimahuira, 2021). To overcome the challenge of analyzing this large number of reviews, sentiment analysis techniques are used. Sentiment analysis makes it possible to measure guest opinions in text data by assigning weights to words, sentences, or pairs of words to determine whether the sentiment expressed is positive or negative (Maulana Herza et al., 2024).

This research utilizes a secondary data-based comparative experimental design. Traveler review data was collected from the TripAdvisor platform, and the performance of three Naïve Bayes algorithm variants (GaussianNB, MultinomialNB, and BernoulliNB) was compared in classifying the sentiment in the data. The main purpose of this classification is to measure the overall guest reviews of Bvlgari Resort Bali and to measure the accuracy of the Naïve Bayes method in performing sentiment classification. This research is expected to make a practical contribution to the management of Bvlgari Resort Bali in understanding the sentiments of their guests and taking necessary actions to improve the overall guest experience (Shiji Group, Unknown).

LITERATURE REVIEW

Previous research conducted by (Fikri et al., 2020)compared the Naïve Bayes and Support Vector Machine (SVM) algorithms in sentiment analysis of 2,654 tweets on Twitter. The research findings show that Naïve Bayes reaches an accuracy threshold of 73.63%, while SVM reaches an accuracy threshold of 70.20%. SVM was used because of its ability to identify the best hyperplane as a separator between two data sets. This hyperplane is known as a support vector, and its purpose is to minimize the distance between data points of each of the aforementioned classes (Yousef & Alali, 2022). On the other hand, Naïve Bayes Classifier (NBC) is a simple yet effective probabilistic classification method in classifying data. It is based on probabilistic theory and the Bayes principle, which assumes that every attribute in the data is independent of every other attribute (naive assumption). Although this assumption is not always true, Naïve Bayes still has the main advantages of ease of use and speed during the training process, especially for large datasets. There are many other studies conducted on sentiment analysis using Naïve Bayes classification. The average research has good accuracy. The accuracy of customer responses through reviews using Naïve Bayes has better results than using TextBlob with an accuracy difference of 2.9% (Permana et al., 2017).

METHODS

To conduct this research, it is necessary to know how data collection procedures and data processing stages are carried out in data preprocessing, and classification modeling using the naive bayes classifier algorithm. The stages for the research method can be seen in the figure below:

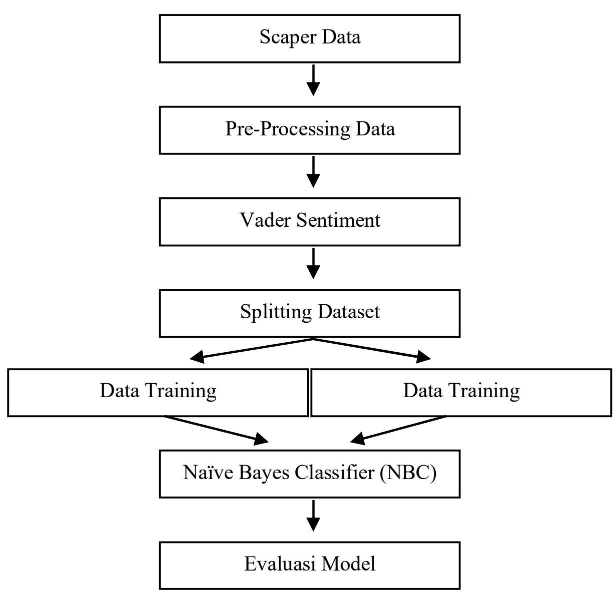

Figure 1. Research Stages Diagram for Sentiment Analysis Using Naïve Bayes

Data Scraper

The data collection process is done by web scraping and using the phyton programming language that is available on google colab. Guest reviews from tripadvisor luxury hotel in Bali, namely Bvlgari Resort Bali, are data taken as data needed for the sentiment analysis process. The data scraping process only focuses on the newest category (latest data), the dataset collected is review data on tripadvisor reviews as many as 1000 datasets.

Data Pre-Processing

Data preprocessing is a stage technique to change unsuitable data into structured data (Fikri et al., 2020). Some data preprocessing steps can be seen in the following figure:

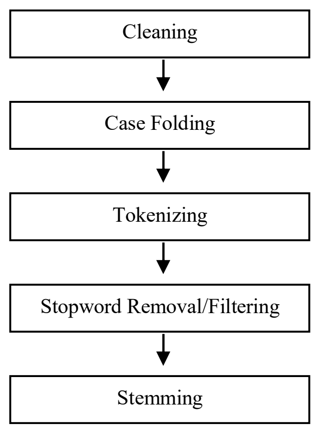

Figure 2. Data Preprocessing Workflow for TripAdvisor Reviews

Vader Sentiment

VADER, which stands for Valence Aware Dictionary and Sentiment Reasoner, is a tool used to analyze sentiment. Sentiment analysis aims to identify whether a text contains positive, negative, or neutral emotions.

Dataset Splitting

Before training the Naïve Bayes model, we need to split the dataset into training data and testing data. The purpose of splitting the dataset is to train the model with part of the data (training set) and test the performance of the model with new data (testing set) that was not seen before. In this case, the dataset is split with a ratio of 80% for training used to train the model and 20% for testing used to test the model.

Naive Bayes Classifier (NBC)

Training data that has gone through the preprocessing and word weighting stages will be input to the training process in applying the naive bayes algorithm (Permana et al., 2017). After going through the frequency calculation stage in each document, the classification stage is carried out using the naive bayes algorithm by calculating the prior probability, then by calculating the conditional probability, and finally calculating the posterior probability.

Evaluation of Three Naive Bayes Models

Model evaluation is performed using several metrics to measure classification performance. These metrics are calculated using the Scikit-learn library in Python. The following is an explanation of each metric:

Accurac

Measures the proportion of total reviews that are correctly predicted by the model. Calculated as (Number of correct predictions)/(Total number of predictions).

Precision

For each sentiment class, precision measures the proportion of reviews predicted as that class that are actually that class. It is calculated as (Number of correct predictions for the class) / (Total predictions for the class).

Recall

For each sentiment class, recall measures the proportion of reviews that actually belong to that class that the model successfully predicts as that class. It is calculated as (Number of correct predictions for the class) / (Total actual reviews in the class).

F1-score

The harmonic mean of precision and recall, providing a balance between the two. Useful when there is class imbalance. Calculated as 2*(Precision*Recall)/(Precision+Recall).

Confusion Matrix

A table that visualizes the performance of the classification model. The rows represent the actual classes, and the columns represent the predicted classes. The elements on the main diagonal represent correct predictions, while the elements off the diagonal represent misclassifications.

In this study, the performance of three variants of the Naïve Bayes algorithm (GaussianNB, MultinomialNB, and BernoulliNB) is compared in classifying the sentiment in the data.

RESULTS AND DISCUSSION

Data Scraper

In this study classify tripadvisor review data of Bvlgari resort Bali guests. Stages to classify review data using the Python programming language which aims to analyze sentiment towards Bvlgari Resort Bali guest satisfaction. At this stage of data collection, a web scrapingg process is carried out to collect datasets obtained from tripadvisor reviews of Bvlgari Resort Bali. The results of scrapping review data on tripadvisor are shown in the figure below:

user/name	publishedDate	rating	text
Tracy	01/03/2025	5	Our experience at Bvlgari Resort Bali was beyond amazing! The highlight of our stay was the outstanding service from Butler Ode
Riska Ms	14/02/2025	4	Spent my birthday here, Ocean Cliff Villa.
Kevin Chung	05/02/2025	5	åœ¨å·´åŽ˜å²›ä½è¿‡æœ€å¥¢åŽçš„é…’åº—ã€é…’åº—æŠŠæˆ‘ä»¬2é—´3äººæˆ¿å‡çº§æˆäº†ä¸¤å§å®¤æµ·æ™¯åˆ«å¢…ã€Ivanå’ŒOw
MMJ	26/01/2025	5	The most upscale paradise hotel in Bali. Everything was simply gorgeous and top notch and staff was amazing ! Views people and
Clio M	26/12/2024	5	I had the pleasure of enjoying breakfast at the Bulgari Hotel Bali, and it was truly an unforgettable experience. The terrace where
Kadek Novie	20/11/2024	1	Surprisingly, the service here falls far short of what I would expect from a luxury hotel. Extending my stay in this room seems like a b
Lyric J	29/10/2024	5	I never write reviews, but this place deserves recognition. The level of service is something you'd expect from a hotel twice the price.
Honest Review	21/09/2024	5	Get an ocean Cliff villa You will never want to leave the villa Pool Monkeys view total relaxation Impeccable service and dining
Roua K	02/09/2024	5	This resort is possibly my favorite of all the resorts/hotels I've been to. I knew it'd be great from the pictures, but the reality
tcoyote	01/09/2024	5	On the cliffs at Uluwatu, Bulgari is apart from the chaos that is Denpasar. The resort tops a steep cliff and site and rooms face
Mary Caroline S	30/08/2024	5	Giving this 5 stars as we booked this on points and were overwhelmed with the beauty of the property and the room. I read these
anna a	19/06/2024	5	Bulgari in Bali far exceeded our expectations. The service was amazing and the staff was so welcoming and helpful. The resort itself
Yan on the Road	16/06/2024	5	è¸é€²å¤¦å‡æ'å¤§å ,ä¸€åˆ»ï¼ŒçœŸæ-£æ„Ÿå—åˆ°å¯§éœï¼Bulgari Resort
Robb L	01/06/2024	5	Our recent stay was simply amazing. Every need met or surpassed. The service and energy of the staff and associates is perhaps the
Molly Chan	27/05/2024	5	We stayed at Bulgari Resort from 23/5 to 26/5 for our 40th wedding anniversary . The moment we checked in until we leave, this
Subhankar Dutta	23/05/2024	4	Situated at one of the most stunning locations in Bali, it is one of the finest resort in Bali, and can easily come in top 5 most luxury
lucyandethel	18/05/2024	5	We have been to the Bulgari Bali several times now over the years and each time we ask ourselves "why go anywhere else?" It is
CHSG	08/05/2024	5	Wir fahren immer nur in die besten Hotel und Resorts auf der Welt, aber das Bulgari Bali Resort hat all unsere Erwartungen
Anthony G	03/05/2024	1	Unfortunately coming from Mandapa Ubud to this refuge was to much of a drop in standards .
Brooke	25/04/2024	5	Oh what a dreamy place! The incredible ocean views from every aspect of the property cannot be beat. The property feels calm an p
Norman Moralejo	23/04/2024	5	What a Gorgeous property
Nicholas	28/01/2024	5	Just a short but great weekend trip jenough to relax and calm down after two busy working weeks in SE Asia. One has to discover
iELM	25/11/2023	5	Beautiful quiet resort with a beautiful garden and a private beach with cable car access. Our butler Lanang is truly one of a kind. Very
llum867	19/11/2023	5	After 5 days in Ubud area descovering the island we booked one night at Bulgari
Charles	02/11/2023	5	Our server Avio at the restaurant at the Bulgari, Uluwatu, Bali provided exceptional service. Avio went above and beyond with his pr
Gusfenton	16/10/2023	5	We have just returned from a 3 night stay at the Bulgari. We have stayed at various resorts in Bali over the years and the location is
Allen19	06/10/2023	5	The Bulgari, Bali is an architectural beauty in a minimalist way perched on a cliff above the Indian Ocean facing south with lush
Jennifer H	01/10/2023	5	Stayed back in 2013. Wonderful experience. Breathtaking views. Breakfast is of highest quality. Huge villas. We loved the Indonesian
Mahardika J	20/09/2023	5	My husband, mom, and I had the privilege of experiencing the exquisite Bvlgari Resort Bali, and it was truly a dreamlike escape!
Pau Costiniano	19/08/2023	4	Dream-like and paradise-like are not enough to describe the experience in staying in one of finest luxury resorts in the world. From p
Spainlatindoctor	17/07/2023	5	perfect peaceful
Anil9154	18/06/2023	5	Spectacular view, comfortable beds, 2 washrooms, sparkling clean, close to our boat tour in the morning. Lots of soft towels. Couldn
SuaSponte	05/06/2023	5	If you are looking for a resort for pure relaxation and beauty, the Bulgari is that resort.we stayed in the cliff side villa and I did not wa
Andrew P	23/05/2023	5	This hotel exceeded our expectations on all levels. The grounds and villas are so beautiful. Everywhere you go, you feel in awe of
Anthony A	11/05/2023	5	This is a lovely resort located on a cliff side in Uluwatu with incredible views. The gardens are perfectly manicured and the staff were
Alessandro Mari... G	05/04/2023	5	Thank you ever so much for having us at Bvlgari Resort Bali, such a prestigious resort. Iâ€™ll take this chance to thank all the staff me

Figure 3. Web Scraping Process of TripAdvisor Reviews for Bvlgari Resort Bali

The dataset collected is tripadvisor Bvlgari Resort Bali review data with a period of May 21, 2010 to March 1, 2025 as much as 1000 data obtained using web scraping. The data taken is data with 1, 2, 3, 4 and 5 star ratings.

Data Pre-Processing

Review data on the tripadvisor application that has been collected totaling 1000 data then preprocessed. The words used in user reviews are text data in an unspoken form so they need to be processed into useful information. The stages that have been carried out in data preprocessing are cleaning, case folding, tokenizing, stopwords, and Stemming which are shown in the table.

Cleaning is the process In this stage, we remove numbers, punctuation marks, and excess spaces. However, in this example sentence there are no numbers or punctuation marks that need to be removed e.g. "The service provided by Bvlgari Resort Bali is perfect1." Becomes "The service provided by Bvlgari Resort Bali is perfect".

Table 1. Example of Data Before and After the Cleaning Process

Before Cleaning	After Cleaning
After 5 days in Ubud area discovering the island we booked one night at Bulgari	After days in Ubud area discovering the island we booked one night at Bulgari
It was a really goergeus experience!!!	It was a really goergeus experience

Case folding is changing all letters into lowercase letters so that there is no difference, such as the word "Perfect" with "perfect". For example, a review with the sentence "The services provided by Bvlgari Resort Bali are perfect" then case folding becomes "the services provided by bvlgari resort bali are perfect".

Table 2. Example of Data Before and After Case Folding

Before Case Folding	After Case Folding
After days in Ubud area discovering the island we booked one night at Bulgari	after days in ubud area discovering the island we booked one night at bulgari
It was a really goergeus experience	it was a really goergeus experience

Tokenizing is the process of breaking down text into small units called tokens into individual words. An example is a review with the sentence "the service provided by bvlgari resort bali is perfect" made into ['service', 'which', 'given', 'bvlgari', 'resort', 'bali;, 'perfect'].

Table 3. Example of Data Before and After Tokenizing

Before Tokenizing	After Tokenizing
after days in ubud area discovering the island we booked one night at bulgari it was a really goergeus experience	['after', 'days', 'in', 'ubud', 'area', 'descovering', 'the', 'island', 'we', 'booked', 'one', 'night', 'at', 'bulgari', 'it', 'was', 'a', 'really', 'goergeus', 'experience']

Stopwords are common words that appear frequently but are not very important for analysis, such as "yang", "diberikan", "di", etc. For example, their usage ['service', 'yang', 'given', 'bvlgari', 'resort', 'bali', 'perfect'] becomes ['service', 'bvlgari', 'resort', 'bali', 'perfect'].

Table 4. Example of Data Before and After Stopword Removal

Before Stopword	After Stopword
['after', 'days', 'in', 'ubud', 'area', 'descovering', 'the', 'island', 'we', 'booked', 'one', 'night', 'at', 'bulgari', 'it', 'was', 'a', 'really', 'goergeus', 'experience']	['days', 'ubud', 'area', 'descovering', 'island', 'booked', 'one', 'night', 'bulgari', 'really', 'goergeus', 'experience']

Stemming is changing a word to its base form, for example ['service', 'bvlgari', 'resort', 'bali', 'perfect'] to bvlgari resort bali perfect service.

Table 5. Example of Data Before and After Stemming

Before Stemming	After Stemming
['days', 'ubud', 'area', 'descovering', 'island', 'booked', 'one', 'night', 'bulgari', 'really', 'goergeus', 'experience']	days ubud area discovering island booked one night bulgari really goergeus experience

Vader Sentiment

After pre-processing is complete, labeling is done using Vader sentiment with the results of positive, negative, or neutral sentiment. The following is the result of Vader Sentiment which can be seen in the image below:

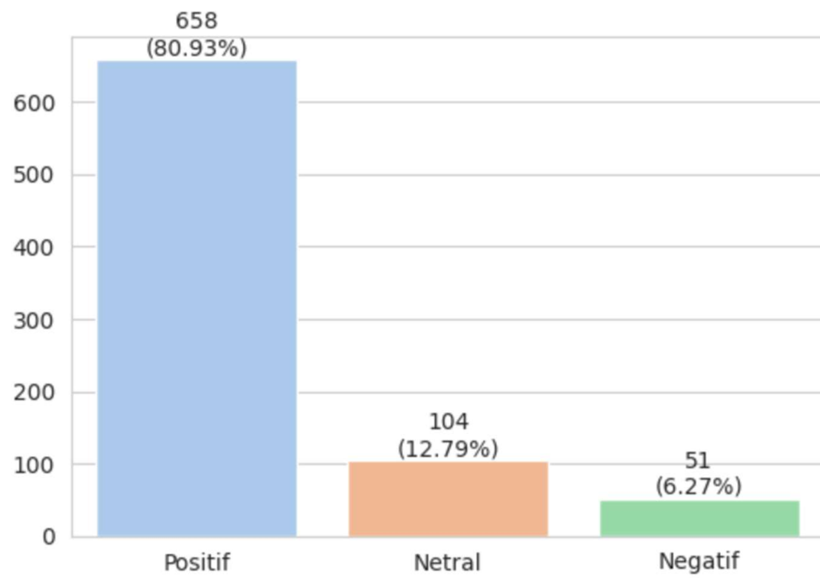

Figure 4. Sentiment Labeling Results Using VADER

Dataset Splitting

Spliting the dataset is carried out by classifying positive and negative sentiments by modeling data which is divided into two parts, namely training data and testing data and then classified using the Naïve Bayes algorithm, the division of training data and testing data is data that already has a class label. The following figure shows the results of dividing the data into 80%: 20% scenario.

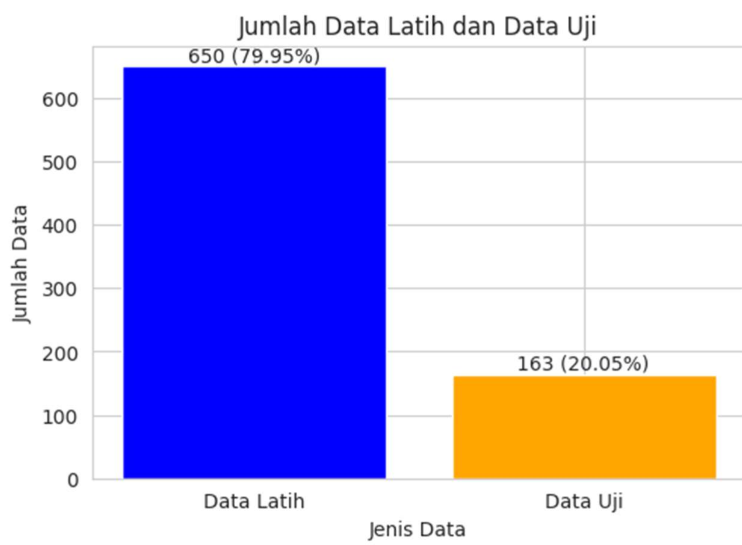

Figure 5. Dataset Split into Training and Testing Sets

After dividing the classification modeling of training data and testing data, Naïve Bayes Classifier (NBC) is then carried out before evaluating.

Naïve Bayes Classifier

Naive Bayes classification here through the stages of Transforming Text into Token Frequency Matrix Calculating Prior Probability ($P(C)$P(C)):

Prior Probabilities	
Sentiment	
Positive	0.809348
Neutral	0.127921
Negative	0.062731

Table 6. Prior Probability Calculation Results for Each Sentiment Class

The prior probability, denoted by P(C), represents the initial probability distribution of each sentiment class (C) in the training dataset before feature observation. Based on the data, the positive sentiment class has the highest prior probability (P(Positive)=0.809348), indicating the prevalence of this class in the training corpus. The neutral sentiment class has a prior probability of P(Neutral)=0.127921, and the negative sentiment class has the lowest prior probability (P(Negative)=0.062731). These prior probabilities are fundamental components in the Naive Bayes classification algorithm, which will then be combined with the feature likelihood probabilities to generate the posterior probabilities of the classes. An unbalanced prior distribution can affect model performance, especially in classes with minority representation.

Next Calculating the Conditional Probability ($P(wi|C)$P(w i|C)) the results are seen in the following figure:

```
Probability Conditional Positive:
ab                0.000091
aback             0.000091
abbandonando      0.000091
abbia             0.000091
abbiamo           0.000091
                    ...
zuvorkommend      0.000091
zuvorkommenden    0.000091
zuwenig           0.000091
zwar              0.000091
zwei              0.000091
Length: 10947, dtype: float64

Probability Conditional Negative:
ab                0.000091
aback             0.000091
abbandonando      0.000091
abbia             0.000091
abbiamo           0.000091
                    ...
zuvorkommend      0.000091
zuvorkommenden    0.000091
zuwenig           0.000091
zwar              0.000091
zwei              0.000091
Length: 10947, dtype: float64

Probability Conditional Neutral:
ab                0.000091
aback             0.000091
abbandonando      0.000091
abbia             0.000091
abbiamo           0.000091
                    ...
zuvorkommend      0.000091
zuvorkommenden    0.000091
zuwenig           0.000091
zwar              0.000091
zwei              0.000091
Length: 10947, dtype: float64
```

Figure 6. Conditional Probability (P(wi|C)) for Each Token in Naïve Bayes Model

The figure above presents the conditional probability P(wi|C) of each token wi for sentiment class C (Positive, Negative, Neutral). The small and uniform probability values (0.000091) for many tokens indicate rare tokens and/or *smoothing* effects. Although individually low, this combination of probabilities is important for Naive Bayes classification. Tokens with differences in probability between classes are more informative.

Then finally Calculate the Posterior Probability ($P(C|w)$P(C|w)) for Each Document with the results in the following figure:

	user/name	publishedDate	rating	steming_data	Compound_Score	Sentiment	posterior_probabilities
0	Tracy	2025-03-01	5	experience bvlgari resort bal beyond amazing h...	0.9931	Positif	{'Positif': 1.0954479018167408e-295, 'Negatif'...
1	Riska Ms	2025-02-14	4	spent birthday ocean cliff villa get room ther...	0.9866	Positif	{'Positif': 0.0, 'Negatif': 0.0, 'Netral': 0.0}
2	Kevin Chung	2025-02-05	5	ivanowenbuggy	0.0000	Netral	{'Positif': 7.393332360289895e-05, 'Negatif': ...
3	MMJ	2025-01-26	5	upscale paradise hotel bal everything simply g...	0.9566	Positif	{'Positif': 9.226829893409754e-98, 'Negatif': ...
4	Clio M	2024-12-26	5	pleasure enjoying breakfast bulgari hotel bal ...	0.9932	Positif	{'Positif': 8.350382581837032e-308, 'Negatif':...

Figure 7. Posterior Probability (P(C|w)) for Each Review Document

The figure shows the posterior probability P(C|w) for each review, i.e. the Naive Bayes model's confidence that the review belongs to sentiment C (Positive, Negative, Neutral) after looking at its words. The posterior_probabilities column displays this value for each class. The sentiment label Sentiment is the class with the highest posterior probability. There is high confidence in the 'Positive' prediction for some reviews, however there are cases of row 1 with zero probability across all classes that need to be investigated.

Evaluation

The data classification process is carried out using probability calculations on sentences in each class to be able to produce predictions and accuracy of the data entered. In order to determine the performance of the naive bayes algorithm, testing was carried out on 163 test data. The classification results will be visualized in the form of a confusion matrix. The following are the results of classification testing using the naive bayes algorithm:

Evaluation with the Naive Bayes Gaussian classification model obtained results as shown below:

```
Confusion Matrix (GaussianNB):
[[  3   0   7]
 [  1   7   8]
 [  0   2 135]]
==================================

Classification Report (GaussianNB):
              precision    recall  f1-score   support

     Negatif       0.75      0.30      0.43        10
      Netral       0.78      0.44      0.56        16
     Positif       0.90      0.99      0.94       137

    accuracy                           0.89       163
   macro avg       0.81      0.57      0.64       163
weighted avg       0.88      0.89      0.87       163

==================================
Accuracy (GaussianNB): 0.8896
```

Figure 8. Gaussian Naïve Bayes Model Evaluation Using Confusion Matrix

Evaluation of the Naive Bayes Gaussian model on 163 test data resulted in an accuracy of 0.89. Confusion matrix and classification report showed good performance on Positive sentiment (precision 0.90, recall 0.99). However, the model is less good at identifying Negative sentiments (precision 0.75, recall 0.30) and has lower recall for Neutral sentiments (recall 0.44). This indicates an imbalance in performance between classes.

Evaluation with the Naive Bayes Multinomial classification model obtained results as shown below:

```
Classification Report (MultinomialNB):
              precision    recall  f1-score   support

     Negatif       1.00      0.20      0.33        10
      Netral       0.50      0.12      0.20        16
     Positif       0.86      0.99      0.92       137

    accuracy                           0.85       163
   macro avg       0.79      0.44      0.48       163
weighted avg       0.83      0.85      0.81       163

===================================
Accuracy (MultinomialNB): 0.8528
===================================
```

Figure 9. Multinomial Naïve Bayes Model Evaluation Using Confusion Matrix

The Multinomial Naive Bayes model achieved an accuracy of 0.85 on the test data. The performance on Positive sentiment (precision 0.86, recall 0.99, F1-score 0.92) is still good. However, the performance on Negative (recall 0.20) and Neutral (recall 0.12) sentiments is very low, indicating the difficulty of identifying these two minority classes. Although the precision for Negative is high (1.00), the low recall indicates many Negative reviews are misclassified as Positive. Comparison with Gaussian Naive Bayes shows the difference in performance between models on different classes.

Evaluation with the Naive Bayes Bernoulli classification model obtained results as shown below:

```
Confusion Matrix (BernoulliNB):
[[  0   5   5]
 [  0   5  11]
 [  0   4 133]]
===================================

Classification Report (BernoulliNB):
              precision    recall  f1-score   support

     Negatif       0.00      0.00      0.00        10
      Netral       0.36      0.31      0.33        16
     Positif       0.89      0.97      0.93       137

    accuracy                           0.85       163
   macro avg       0.42      0.43      0.42       163
weighted avg       0.79      0.85      0.81       163

===================================
Accuracy (BernoulliNB): 0.8466
```

Figure 10. Bernoulli Naïve Bayes Model Evaluation Using Confusion Matrix

The Bernoulli Naive Bayes model achieved an accuracy of 0.85. The performance on Positive sentiment (precision 0.89, recall 0.97, F1-score 0.93) is still relatively good. However, the model failed to predict Negative sentiments at all (precision and recall 0.00). The performance on Neutral sentiment is also low (precision 0.36, recall 0.31). The moderate overall accuracy is driven by the prediction success on the predominantly Positive class. The model showed significant weakness in identifying minority sentiments (Negative and Neutral).

Evaluation of three Naive Bayes models showed varying performance in the sentiment classification task. The GaussianNB and MultinomialNB models showed better accuracy (0.89 and 0.85) than BernoulliNB (0.85), especially in identifying Negative and Neutral sentiments although it is still a challenge. All three models consistently excel in predicting Positive sentiment which is the majority class. However, significant weaknesses were seen in the identification of minority sentiments, especially in the BernoulliNB model which failed to predict Negative sentiments. The selection of the most suitable Naive Bayes model depends on the priority between precision and recall for each sentiment class, as well as the characteristics of the data distribution. For this unbalanced dataset, handling minority classes needs to be a major focus in further model development.

The imbalance of the data, where positive sentiments far outnumber negative and neutral sentiments, is a challenge in this study. For future research, it is recommended to apply oversampling techniques (e.g., SMOTE) to oversample minority sentiments or use *class weighting* to give more weight to minority sentiments during model training. These techniques can help improve the model's performance in identifying negative and neutral sentiments.

Wordcloud visualization

To provide further visualization of the words that appear most frequently in reviews with a particular sentiment, we present word clouds for both positive and negative sentiments.

Visualizing key words through word clouds can provide intuitive insights into the aspects most commonly associated with positive and negative sentiment. Here's an image of a positive sentiment word cloud:

Figure 11. Word Cloud of Positive Sentiment Reviews for Bvlgari Resort Bali

The image above is a word cloud depicting the most frequent words in positively labeled reviews. The size of the words is proportional to their frequency in the corpus of positive reviews. It can be seen that words like 'villa', 'stay', 'hotel', 'great', 'food', 'room', 'service', 'beach', 'resort', and 'staff' dominate this visualization. This shows that aspects such as accommodation (villa, hotel, room), service quality (service, staff), facilities (beach, resort), and general experience (great stay, food) are the main focus in the positive reviews.

The positive sentiment word cloud analysis revealed an emphasis on a pleasant stay, with words such as 'amazing', 'beautiful', 'excellent', 'nice', and 'wonderful' also standing out. This is in line with the classification results which show the model's good performance in identifying positive sentiments. In contrast, the negative sentiment word cloud below:

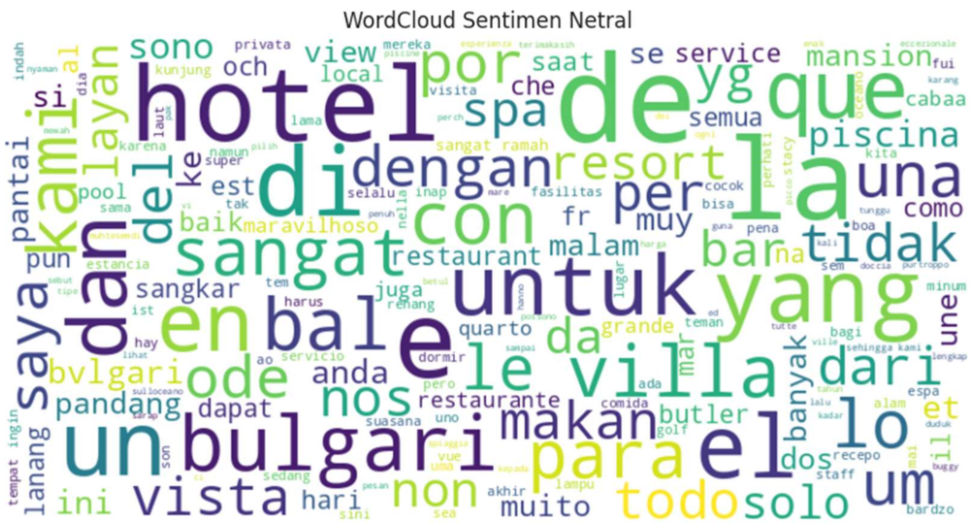

Figure 12. Word Cloud of Negative Sentiment Reviews for Bvlgari Resort Bali

The word cloud for reviews with negative sentiment (image below) shows a different focus. Words such as 'nicht' (no), 'war' (was/is), 'keine' (no), 'aber' (but), 'service', 'zimmer' (room), 'hotel', 'restaurant', 'pool', and 'bad' have a high frequency. This indicates that complaints in negative reviews are often related to service issues, room quality, restaurant experiences, and facilities such as swimming pools.

The appearance of German words ('nicht', 'war', 'keine', 'aber', 'zimmer') also indicates the proportion of negative reviews in the language. Comparison with the positive word cloud clearly shows the different vocabulary used to express negative experiences.

CONCLUSIONS

Sentiment analysis of TripAdvisor reviews on luxury resorts in Bali using three Naïve Bayes models showed mixed results. GaussianNB achieved the highest accuracy (0.89), excelling in identifying positive sentiments but limited in negative and neutral sentiments. MultinomialNB (accuracy 0.85) showed a similar pattern BernoulliNB (accuracy 0.85) was effective on positive but failed on negative.

The positive sentiment word cloud highlights the high frequency of words such as 'villa', 'stay', 'hotel', 'great', 'food', 'service', 'beach', and 'resort'. These aspects, which are most often associated with positive reviews, can be a key reference for the management of this resort and other luxury hotels in maintaining and improving the quality of services and facilities most valued by customers. Meanwhile, negative word clouds indicate potential areas for improvement. This study confirms the value of big data-based sentiment analysis as a strategic tool for the hospitality industry.

The implications of this research are not limited to luxury resorts in Bali. The hospitality industry in general can utilize sentiment analysis to understand customer satisfaction, identify areas for improvement, and make strategic decisions. For example, other hotels can use this approach to analyze reviews on online platforms, benchmark themselves against competitors, and adjust their services to meet customer expectations.

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