SENTIMENT ANALYSIS ON SOCIAL MEDIA DATA USING LOGISTIC REGRESSION: A MACHINE LEARNING APPROACH

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DATA SCIENCE INTERNSHIP PROJECT REPORT

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INTRODUCTION:

The proliferation of social media platforms has generated an enormous volume of user-generated content, offering valuable insights into public sentiment on various topics. Analysing this sentiment effectively is crucial for businesses, policymakers, and researchers to understand public opinion, identify trends, and make informed decisions.

Sentiment analysis, a subfield of natural language processing (NLP), involves determining the emotional tone behind a body of text. This project aims to leverage the power of logistic regression, a robust and interpretable machine learning technique, to perform sentiment analysis on social media data.

Logistic regression is a statistical method used for binary classification tasks, making it well-suited for distinguishing between positive and negative sentiments. Its simplicity, efficiency, and ease of implementation have made it a popular choice for various classification problems in NLP.

In this project, we will collect a diverse dataset of social media posts from platforms such as Twitter, Facebook, and Instagram. The data will undergo preprocessing steps, including tokenization, removal of stop words, and stemming, to prepare it for analysis.

We will train a logistic regression model on a labelled dataset, where each post is tagged with a sentiment label (positive or negative). The model's performance will be evaluated using metrics such as accuracy, precision, recall, and F1-score. Additionally, we will perform hyperparameter tuning to optimize the model and improve its predictive capabilities.

By the end of this project, we aim to demonstrate the effectiveness of logistic regression in sentiment analysis and provide insights into the prevailing sentiments expressed on social media. This analysis has the potential to inform marketing strategies, public relations efforts, and policy-making processes by highlighting the public's emotional responses to various issues.

AIM OF THE PROJECT:

This project aims to develop a machine learning model using logistic regression to analyze and classify sentiment in social media data. This involves preprocessing the data, training the model, and evaluating its performance to effectively distinguish between positive and negative sentiments expressed in user-generated content.

LITERATURE SURVEY:

A) Sentiment analysis:

Sentiment Analysis, also known as opinion mining, is a technique used to determine the emotional tone behind a series of words, used to gain an understanding of the attitudes, opinions, and emotions expressed within an online mention.

It involves the use of natural language processing (NLP), text analysis, and computational linguistics to identify and extract subjective information from text data. It has become increasingly significant with the advent of social media. Various techniques have been employed to tackle this problem, ranging from traditional machine learning methods to advanced deep learning approaches.

Companies use sentiment analysis to understand customer opinions about their products or services, enabling them to improve customer satisfaction and tailor their offerings. Analysing trends and public sentiment can help businesses understand market needs and consumer preferences. Organizations track public sentiment on social media platforms to gauge the impact of marketing campaigns, product launches, and public relations efforts. Sentiment analysis helps in understanding public opinion about political issues, candidates, and policies.

B) Logistic Regression:

Logistic regression is a statistical method for analysing datasets in which there are one or more independent variables that determine an outcome. The outcome is measured with a dichotomous variable (in which there are only two possible outcomes).

It is used extensively in binary classification problems, such as spam detection, disease diagnosis, and sentiment analysis. Logistic regression remains a popular choice due to its simplicity, interpretability, and competitive performance in many classification tasks, particularly when

combined with appropriate feature engineering and preprocessing techniques.

- **Binary Classification:** Logistic regression predicts the probability that a given input belongs to a certain class. For binary classification, it models the probability that a given input belongs to the positive class.
- **Sigmoid Function:** The core of logistic regression is the logistic function (sigmoid), which maps any real-valued number into a value between 0 and 1, representing probability.

$$\sigma(z)= 1/1+e -z$$

where zz is a linear combination of input features (i.e., $z=\beta 0+\beta 1x1+\beta 2x2+\ldots+\beta nxnz=\beta 0+\beta 1x1+\beta 2x2+\ldots+\beta nxn$).

C) Random Forest

Random forest is an ensemble learning method that constructs multiple decision trees and merges their predictions to improve accuracy and prevent overfitting. Each tree is built from a random subset of the data and features, ensuring diversity among the trees.

Random forest is highly effective in handling complex datasets with non-linear relationships and interactions among features. It is robust, easy to use, and typically offers high performance in various machine learning tasks, including sentiment analysis.

For classification, the prediction of the random forest model is determined by a majority vote of the constituent decision trees.

$y^=\text{mode}(y1,y2,\ldots,yn)y^=\text{mode}(y1,y2,\ldots,yn)$

D) Linear Regression

Linear regression is a fundamental statistical method used for predictive analysis. It models the relationship between a dependent variable and one or more independent variables by fitting a linear equation to observed data. Despite its widespread use, linear regression is not well-suited for classification tasks like sentiment analysis because it assumes a continuous output. Its performance in sentiment analysis is typically inferior to methods specifically designed for classification. For this reason, linear regression is generally not preferred in sentiment analysis projects.

For a simple linear regression with one independent variable xx and one dependent variable yy, the model can be represented as:

$y=\beta 0+\beta 1x+\epsilon y=\beta 0+\beta 1x+\epsilon$

Where:

- yy is the dependent variable.

- xx is the independent variable.
- $\beta 0\beta 0$ is the intercept.
- $\beta 1\beta 1$ is the slope.
- $\epsilon\epsilon$ is the error term.

E) Support Vector Machines (SVM)

Support Vector Machines are a powerful classification technique that aims to find the optimal hyperplane that maximizes the margin between different classes in the feature space. SVMs are effective in high-dimensional spaces and have been widely used in sentiment analysis due to their robustness in handling various types of data.

However, SVMs can be computationally intensive, especially with large datasets, and selecting the right kernel and regularization parameters can be challenging.

Given a dataset $(xi,yi)(xi,yi)$, where $xixi$ represents feature vectors and $yiyi$ represents class labels:

$\min w,b1/2||w||\text{^}2+C\sum i=1N\xi i$

subject to $yi(w\cdot xi+b)\geq 1-\xi i\text{and}\xi i\geq 0\text{subject to }yi(w\cdot xi+b)\geq 1-\xi i\text{and}\xi i\geq 0$

F) XGBoost

XGBoost, or Extreme Gradient Boosting, is an advanced implementation of gradient boosting algorithms. It has gained popularity for its efficiency, accuracy, and scalability. XGBoost builds an ensemble of trees in a sequential manner, optimizing for the best split at each step.

It handles missing values and overfitting better than many other machine learning algorithms. XGBoost has shown superior performance in various machine learning competitions, including sentiment analysis tasks. However, it requires careful parameter tuning and significant computational resources.

XGBoost minimizes a regularized objective function LL composed of a loss function $l(yi,y\text{^}i)$and a regularization term $\Omega(f)$:

$L=\sum i=1nl(yi,y\text{^}i)+\sum k=1K\Omega(fk)$

Where:

- $y\text{^}iy\text{^}i$ is the predicted value for sample ii.
- $yiyi$ is the true label for sample ii.
- $fkfk$ represents the kk-th tree in the ensemble.
- $\Omega(fk)\Omega(fk)$ is the regularization term that penalizes the complexity of the trees.

G) Naive Bayes

Naive Bayes is a probabilistic classifier based on Bayes' theorem with the assumption of independence between features. It is particularly known for its simplicity and effectiveness in text classification tasks, including sentiment analysis.

Despite its strong assumptions, Naive Bayes performs surprisingly well in many cases. However, it may struggle with more complex patterns and dependencies in data compared to more sophisticated algorithms.

Given a dataset with features $X=\{x1,x2,\ldots,xn\}X=\{x1,x2,\ldots,xn\}$ and class labels YY, the probability of a class cc given the features is calculated using Bayes' theorem:

$P(c|X)=P(X|c)\cdot P(c)/P(X)$

NEED AND SCOPE OF THE PROJECT:

Need:

- To harness the vast amount of sentiment-rich data available on social media for actionable insights. Social media platforms host a wealth of user-generated content, offering valuable insights into public sentiment on various topics.
- Analysing this sentiment can provide businesses, policymakers, and researchers with actionable insights to inform decision-making processes.
- To provide a cost-effective and efficient sentiment analysis tool that can be easily implemented and interpreted.
- To aid businesses, policymakers, and researchers in understanding public opinion and making informed decisions.
- Sentiment analysis aids in assessing the effectiveness of marketing campaigns by tracking how consumers perceive brands, products, or services.
- Understanding public sentiment helps marketers tailor their messaging and strategies to resonate with their target audience more effectively.

Scope:

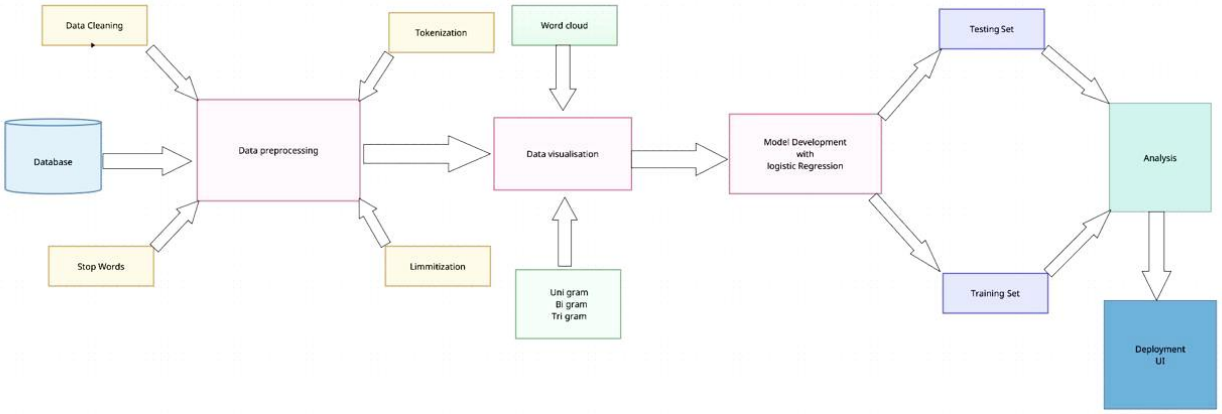
- Collecting a diverse dataset of social media posts from platforms such as Twitter, Facebook, and Instagram.
- Preprocessing the data to remove noise, including URLs, mentions, hashtags, and special characters, and performing text normalization techniques.

- Implementing a logistic regression model to classify sentiments as positive or negative based on the preprocessed data.
- Exploring feature engineering techniques to enhance the model's performance, such as using Bag of Words (BoW), TF-IDF, or word embeddings.
- Evaluating the model's performance using standard metrics such as accuracy, precision, recall, and F1-score.
- Conducting cross-validation to ensure the model generalizes well to unseen data and is robust against overfitting.
- Deploying the trained model to predict sentiment on new social media data, integrating it into applications or systems for real-time sentiment analysis.

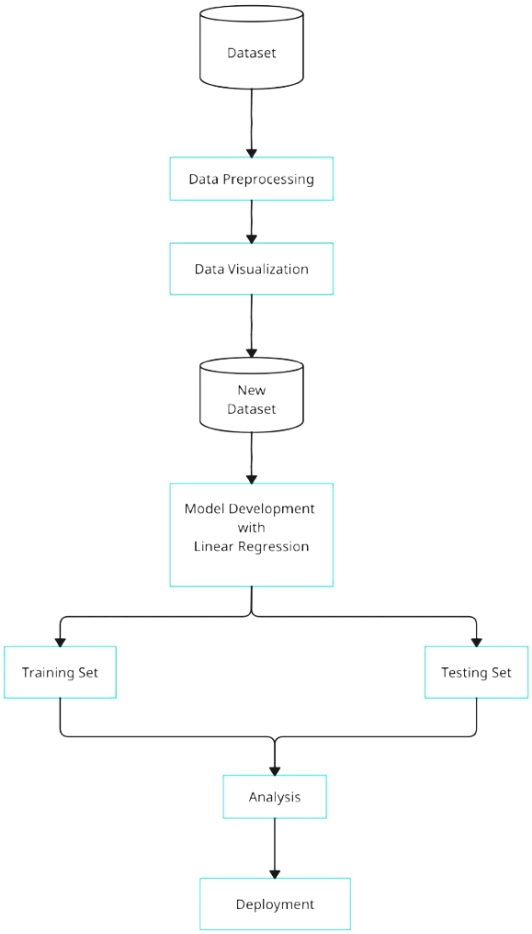
JUSTIFICATION OF ALGORITHM:

- It is straightforward to implement and understand, making it accessible for a wide range of users.
- Logistic regression requires less computational power compared to complex deep learning models, making it suitable for quick analyses.
- The model provides clear insights into the relationship between features and the predicted outcome, which is valuable for understanding the factors driving sentiment.
- With proper feature engineering and preprocessing, logistic regression can achieve competitive performance in sentiment analysis tasks, especially on moderately sized datasets.

SYSTEM ARCHITECTURE:



FLOWCHART:



MODULE DESCRIPTION:

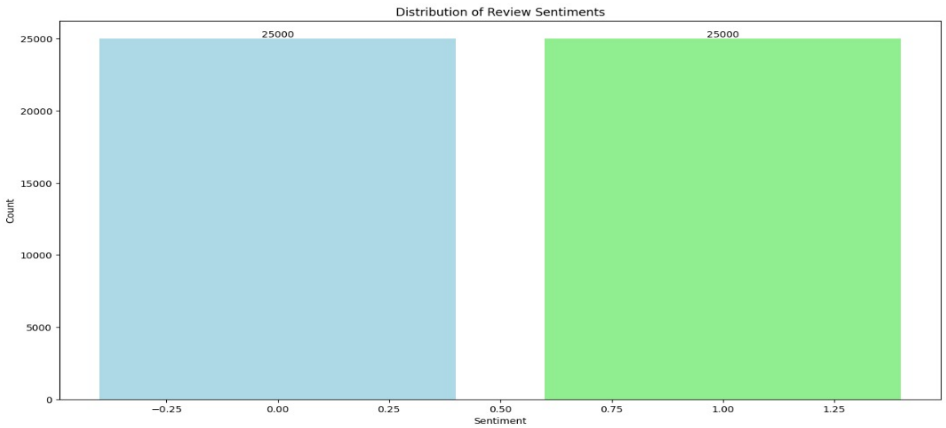
MODULE-1: DATA COLLECTION, PREPROCESSING & VISUALIZATION

In this module, the primary focus is on gathering and preparing the raw data for analysis. This involves some important steps like data collection, data preprocessing, and data visualization.

Data collection:

- We had taken the twitter movie reviews dataset from Kaggle which contains around 50,000 sentiment review tweets data and stored the collected data in a structured format (CSV format).
- Overall collection of tweets was split in the ratio of 80:20 into training and testing data.

CLASS 0 (NEGATIVE SENTIMENT)	CLASS 1 (POSITIVE SENTIMENT)
25000	25000



Dataset link: https://www.kaggle.com/datasets/lakshmi25npathi/imdb-dataset-of-50k-movie-reviews

Data Preprocessing:

The data preprocessing function **data_cleaning(text)** performs several essential tasks to prepare the text data for sentiment analysis.

Initially, it converts all text to lowercase to ensure consistency in word representations. Subsequently, it removes non-alphabetic characters and punctuation marks from the text, effectively eliminating noise that could interfere with the analysis.

Tokenization is then applied to break down the text into individual words or tokens, facilitating further processing.

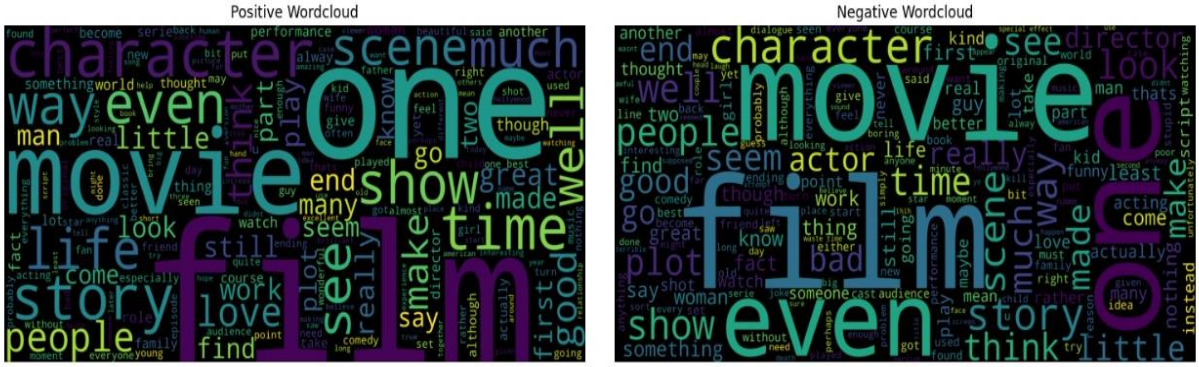
Stop words, which are common words that often carry little semantic meaning, are removed to reduce dimensionality and focus on significant terms.

Finally, **lemmatization** is performed to reduce words to their base or root form, ensuring that different variations of the same word are treated as identical. This comprehensive preprocessing pipeline results in a cleaned and standardized dataset, ready for use in training sentiment analysis models. The function returns a new data frame containing the original tags (labels) associated with the cleaned text, preserving the context necessary for supervised learning.

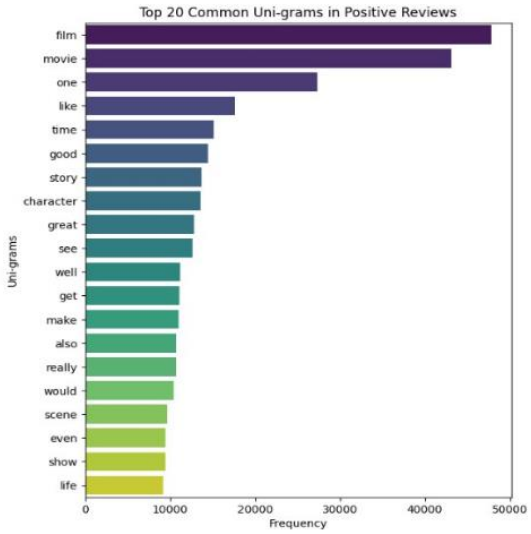
Overall, this preprocessing approach ensures that the sentiment analysis models can effectively capture the underlying sentiment expressed in social media posts while minimizing the impact of irrelevant noise and variability in the data.

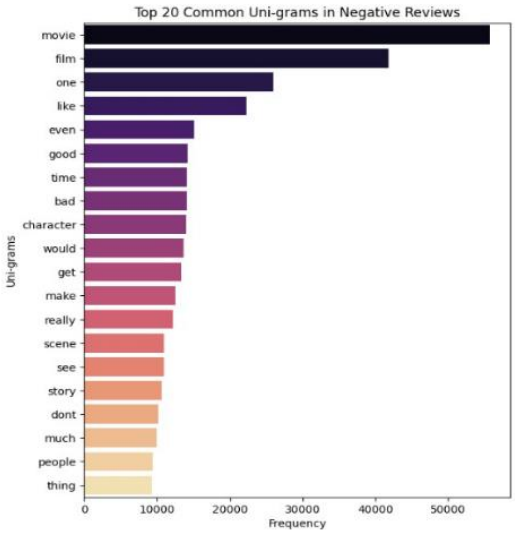
Data Visualization:

- We have Used data visualization techniques to understand the distribution and patterns in the data in our dataset
- Employing tools such as word clouds, bigram charts, and histograms to visualize common words, sentiment distribution, and other key insights.

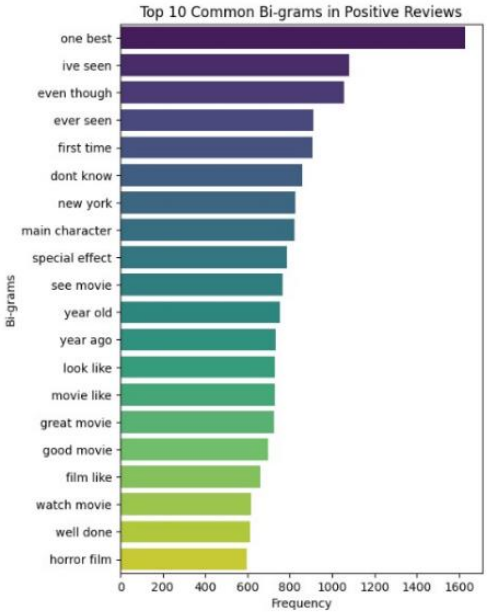


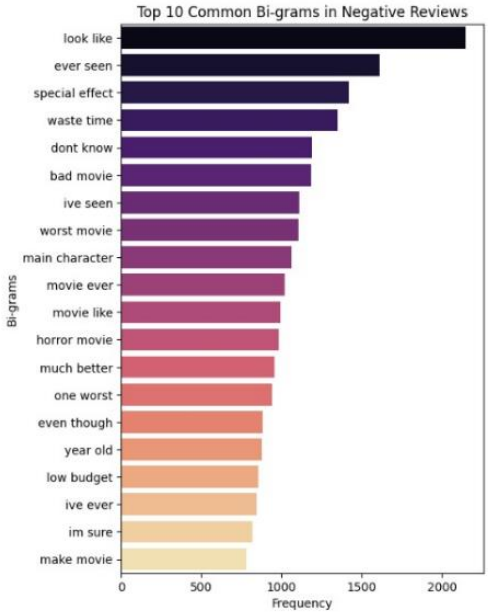
Word cloud



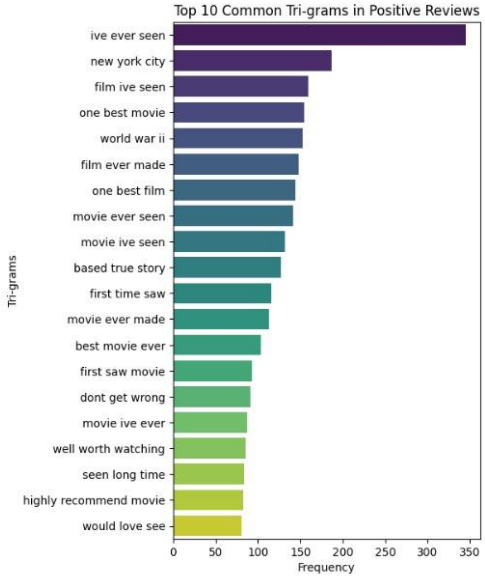


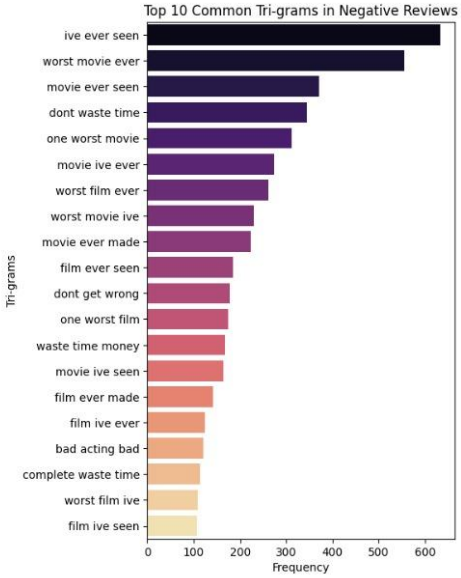
Uni grams





Bi grams


Top 10 Common Tri-grams in Positive Reviews
ive ever seen
new york city
film ive seen
one best movie
world war ii
film ever made
one best film
movie ever seen
movie ive seen
based true story
first time saw
movie ever made
best movie ever
first saw movie
dont get wrong
movie ive ever
well worth watching
seen long time
highly recommend movie
would love see
Tri-grams
0
50
100
150
200
250
300
350
Frequency


Top 10 Common Tri-grams in Negative Reviews
ive ever seen
worst movie ever
movie ever seen
dont waste time
one worst movie
movie ive ever
worst film ever
worst movie ive
movie ever made
film ever seen
dont get wrong
one worst film
waste time money
movie ive seen
film ever made
film ive ever
bad acting bad
complete waste time
worst film ive
film ive seen
Tri-grams
0
100
200
300
400
500
600
Frequency

Tri grams

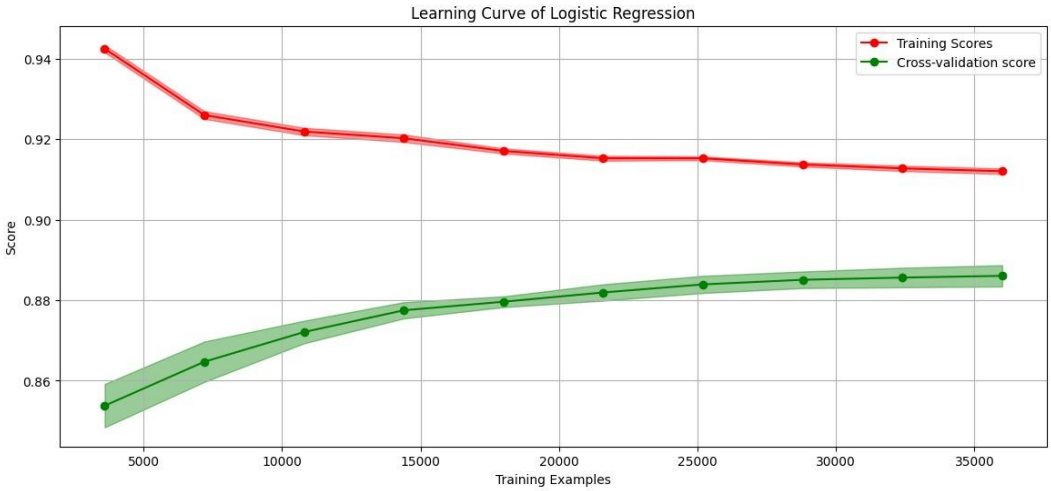
MODULE-2: MODEL DEVELOPMENT AND TRAINING

Model Development:

- This module focuses on building and training machine learning models to perform sentiment analysis.
- We have also utilized libraries such as scikit-learn, TensorFlow, or Keras.
- We have also chosen some other appropriate machine learning algorithms such as Support Vector Machine (SVM), Random Forest, Naive Bayes, and XGBoost and linear regression along with logistic regression to compare the results with them.
- We had trained the selected models on the pre-processed dataset.

Model Training:

- We had trained the individual models (i.e., logistic regression, Support Vector Machine (SVM), Random Forest, Naive Bayes, and XGBoost and linear regression) on the resampled dataset.
- We also used cross-validation to assess model performance and ensure robustness.

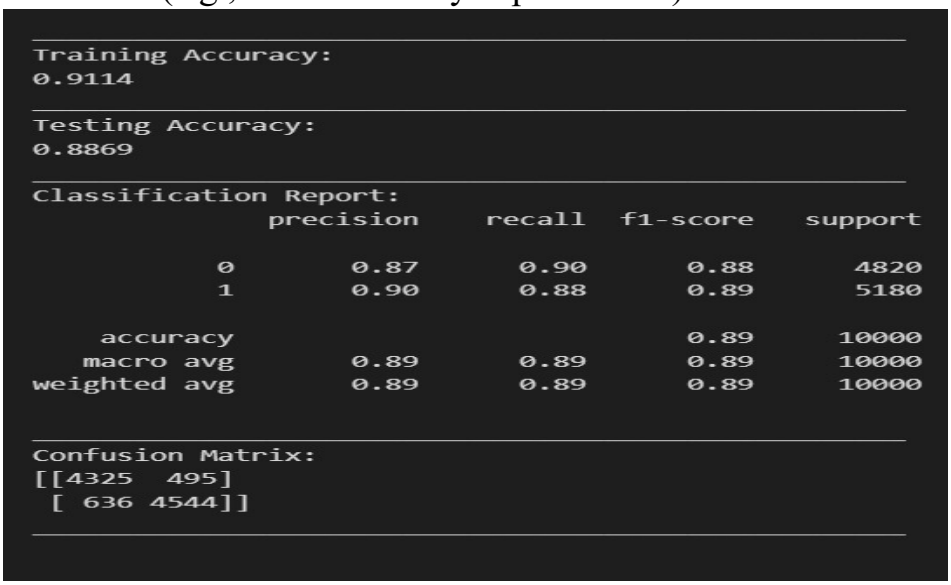


- The learning curve of a logistic regression model depicts its performance (usually measured by error) as the size of the training data increases. It helps diagnose bias-variance trade-off and identify potential issues with the model

MODULE-3: MODEL EVALUATION AND COMPARISON

Model Evaluation:

- Summarizing the evaluation metrics to highlight logistic regression's strengths, such as its interpretability and efficiency, against the complex models which may have slightly better performance but at the cost of interpretability.
- Discussing scenarios where logistic regression is preferable (e.g., when model interpretability is crucial) versus when more complex models might be chosen (e.g., when accuracy is paramount).



```
Training Accuracy:
0.9114

Testing Accuracy:
0.8869

Classification Report:
              precision    recall  f1-score   support

           0       0.87      0.90      0.88      4820
           1       0.90      0.88      0.89      5180

    accuracy                           0.89     10000
   macro avg       0.89      0.89      0.89     10000
weighted avg       0.89      0.89      0.89     10000


Confusion Matrix:
[[4325  495]
 [ 636 4544]]
```

Model Comparison:

- Although, some algorithms overcome the individual metrics of the logistic regression. But other than logistic regression, remaining algorithms show huge difference between the training and testing metrics
- Logistic Regression has a higher training accuracy compared to all other algorithms except Random Forest and also has a higher testing accuracy compared to Naive Bayes, Linear Regression, SVM.
- Logistic Regression is a relatively interpretable algorithm, meaning it's easier to understand how it makes predictions. This can be important in some cases.
- Logistic Regression is a versatile and well-performing algorithm that can be a good choice for many classification tasks.

MODULE-4: MODEL ANALYSIS AND DEPLOYMENT

This module focuses on the in-depth analysis of the logistic regression model and its deployment for real-world sentiment analysis applications. The logistic regression model's performance is further scrutinized by comparing it with the other models and highlighting its practical benefits.

Model Analysis:

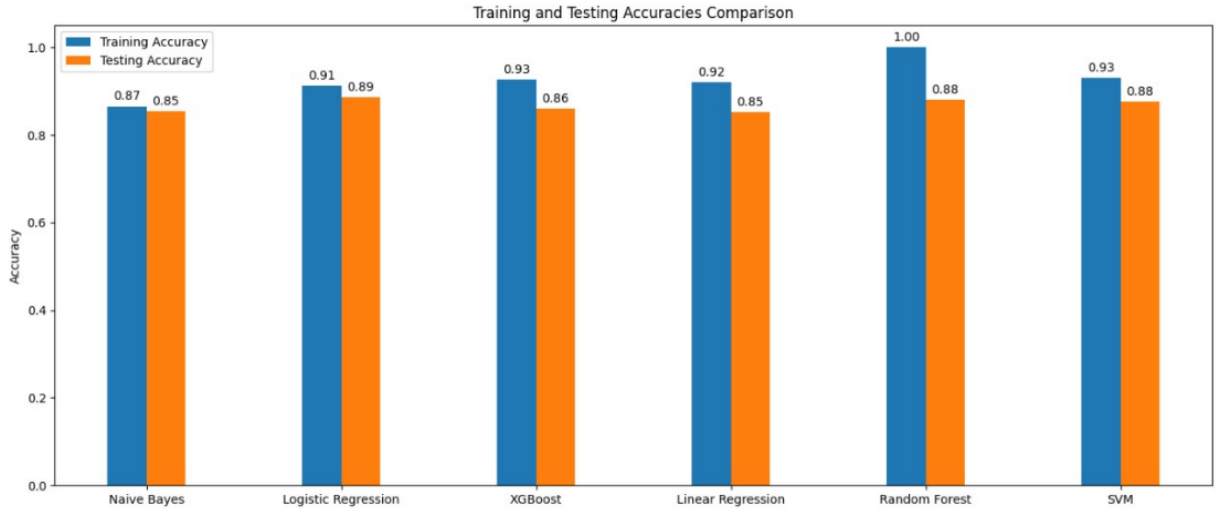
- This module is dedicated to evaluating the performance of the logistic regression model in comparison with other individual models such as Support Vector Machine (SVM), Random Forest, Naive Bayes, XGBoost, and Linear Regression.
- This comparative analysis helps identify the strengths and weaknesses of each model in the context of sentiment analysis.
- We had evaluated our models with performance metrics like accuracy, precision, recall, F-1 score. A confusion matrix is generated for each model to visualize and understand their classification performance. It shows the true positives, true negatives, false positives, and false negatives.

- **Accuracy** provides the proportion of correctly classified instances. $Accuracy = True\ Positives + True\ Negatives / Total$

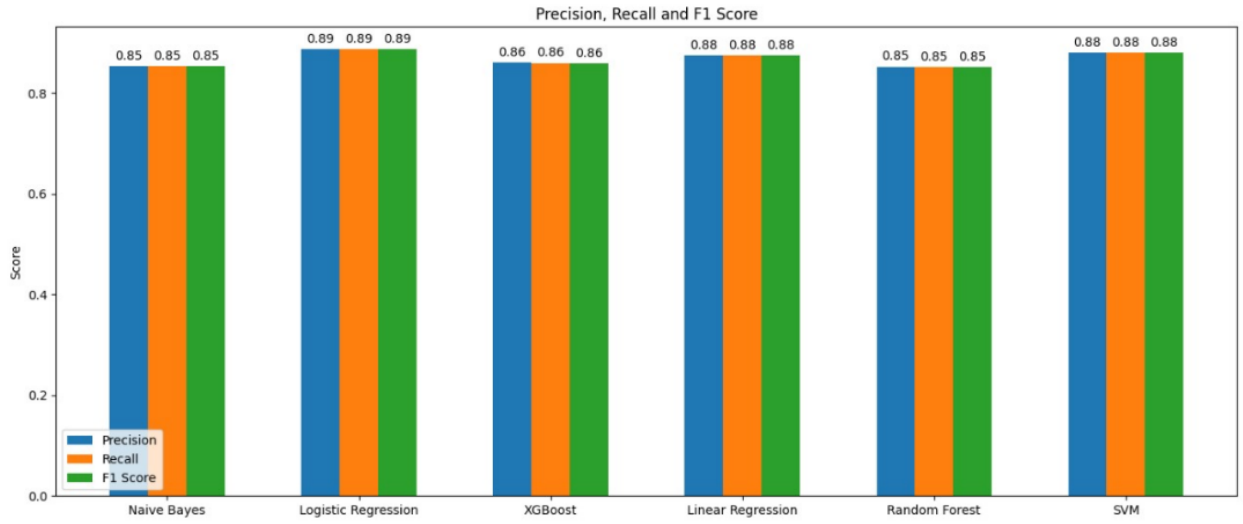
- **Precision** focuses on the accuracy of positive predictions. $Precision = True\ Positives / TruePositives + FalsePositives$

- **Recall (Sensitivity or True Positive Rate)** measures the proportion of correctly predicted positive instances among all actual positive instances. $Recall = True\ Positives / (TruePositives + FalseNegatives)$

- **F1 Score** is the harmonic mean of precision and recall. $F1Score = 2 * (Precision * Recall) / Precision + Reacall$



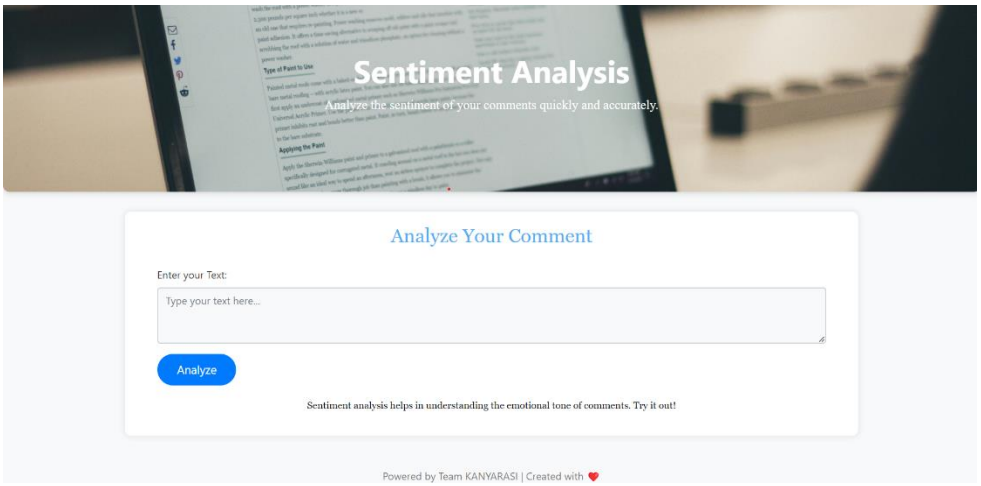
Accuracy Score



Precision, Recall and F-1 Score

Model Deployment:

- We had saved the logistic regression model using formats like Pickle for easy deployment.
- We had Developed a RESTful API using Flask to serve the logistic regression model, enabling real-time sentiment analysis.



CONCLUSION:

This project demonstrates the application of logistic regression for sentiment analysis on social media data, showcasing its effectiveness in classifying sentiments as positive or negative. By systematically collecting, preprocessing, and visualizing social media data, we established a robust pipeline for sentiment analysis. The logistic regression model, known for its simplicity and interpretability, was trained and evaluated against other models like Support Vector Machine (SVM), Random Forest, Naive Bayes, and XGBoost. Our comparative analysis highlighted that while logistic regression provides valuable insights and competitive performance, more complex models can offer slight improvements in accuracy at the cost of interpretability.

The evaluation metrics, including accuracy, precision, recall, F1-score, affirmed the logistic regression model's suitability for this task, particularly when interpretability and efficiency are crucial. The model was successfully deployed, demonstrating its practical application in real-time sentiment analysis scenarios. Overall, the project underscores the importance of balancing model complexity with practical needs, advocating for logistic regression as a viable choice for sentiment analysis in many contexts.

Future Work:

Future work will focus on several key areas to enhance and expand the capabilities of the sentiment analysis model:

1. Data Expansion: Incorporate a larger and more diverse dataset from multiple social media platforms to improve the model's generalizability and robustness.
2. Feature Engineering: Explore advanced feature extraction techniques, such as deep learning-based embeddings (e.g., BERT or GPT embeddings), to capture more nuanced textual information.
3. Model Ensemble: Develop and evaluate ensemble methods that combine the strengths of multiple models, potentially improving overall accuracy and robustness.
4. Real-Time Analysis: Optimize the deployment pipeline for real-time sentiment analysis, ensuring low latency and high throughput to handle large volumes of social media data efficiently.
5. Multilingual Analysis: Extend the model's capabilities to handle multilingual data, enabling sentiment analysis across different languages and expanding its applicability globally.

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