**Automated-review-rating-system**

The Automated Review Rating System is a Python-based application designed to analyse user-generated reviews and predict corresponding ratings using natural language processing and machine learning techniques. It streamlines the feedback analysis process for platforms such as e-commerce websites, hospitality services, or educational portals.

**Example Use Case**

Imagine a hotel receives hundreds of guest reviews daily. Manually reading and scoring each one is time-consuming and inconsistent. With this system:

- Textual reviews like “The rooms were spotless and staff was friendly” are automatically interpreted using sentiment analysis.

- The system predicts a 4.5-star rating based on language tone and keyword intensity.

- Review summaries and rating predictions are visualized for the management team to improve service.

This helps businesses uncover hidden insights, maintain consistent feedback metrics, and improve customer experience based on real-time review data.

**Project Overview and Objective**

This project aims to develop an automated system that predicts product review ratings (1 to 5 stars) based on the text of the review. Using machine learning techniques, the system analyses textual review data to learn patterns and accurately estimate the star rating.

The objective is to build a clean, balanced dataset, apply appropriate pre-processing, and train baseline models using text vectorization methods for initial prototyping.

**Dataset Description**

The dataset consists of customer product reviews collected from CSV file. Each review contains a text field (Text) and an associated rating (1 to 5 stars). The data varies in quality with noise such as URLs, HTML tags, emojis, and variable review lengths.

**Pre-processing Steps**

Text Cleaning: Convert reviews to lowercase; remove URLs, HTML tags, punctuation, emojis, and special characters.

**Initial Cleaning**

Remove missing ratings or reviews

df = df.dropna(subset=['Text', 'Score'])

**Lowercase, strip punctuation, remove short reviews**

df['Text'] = df['Text'].str.lower().str.replace('[^a-z ]', '', regex=True)

df = df[df['Text'].str.len() > 10]

df = df.drop\_duplicates()

**Remove duplicates**

df = df.drop\_duplicates()

**Clean review text: lowercase, remove non-letters**

df['Text'] = df['Text'].str.lower().str.replace('[^a-z ]', '', regex=True)

**Remove reviews shorter than 10 characters**

df = df[df['Text'].str.len() > 10]

**Convert ratings to integer, if they aren't already**

df['Score'] = df['Score'].astype(int)

**Save cleaned data**

df.to\_csv('data/cleaned\_dataset/cleaned\_data.csv', index=False)

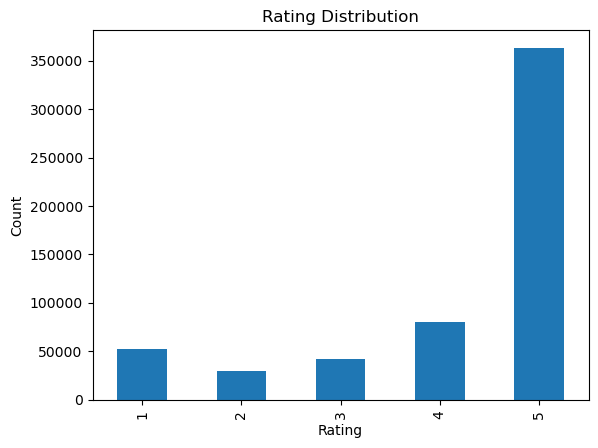
**Data Analysis & Visualization**

df['Score'].value\_counts().sort\_index().plot(kind='bar', title='Rating Distribution')

plt.xlabel('Rating')

plt.ylabel('Count')

plt.show()



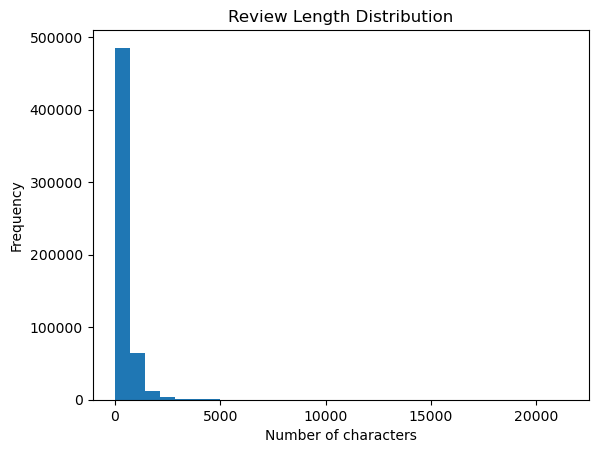
**Review Length Distribution**

df['review\_length'] = df['Text'].str.len()

df['review\_length'].plot(kind='hist', bins=30, title='Review Length Distribution')

plt.xlabel('Number of characters')

plt.show()

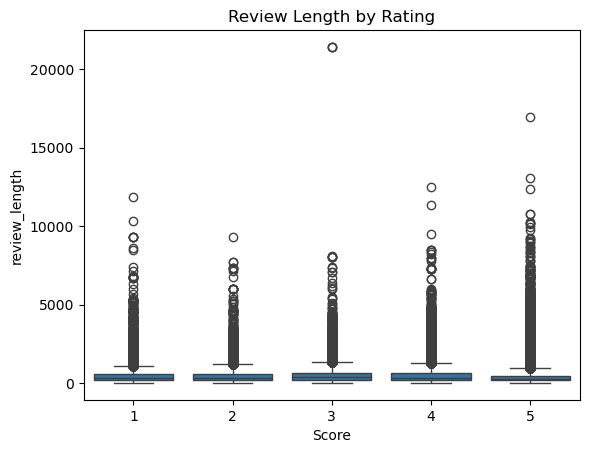


**Review Length by Rating**

sns.boxplot(x='Score', y='review\_length', data=df)

plt.title('Review Length by Rating')

plt.show()



**Violin plots**

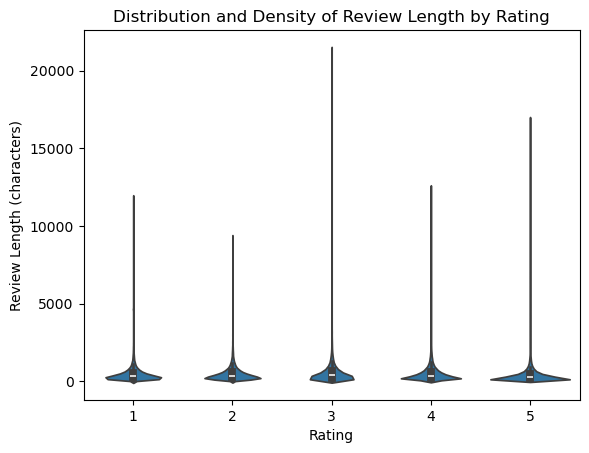
sns.violinplot(x='Score', y='review\_length', data=df, inner='box')

plt.title('Distribution and Density of Review Length by Rating')

plt.xlabel('Rating')

plt.ylabel('Review Length (characters)')

plt.show()



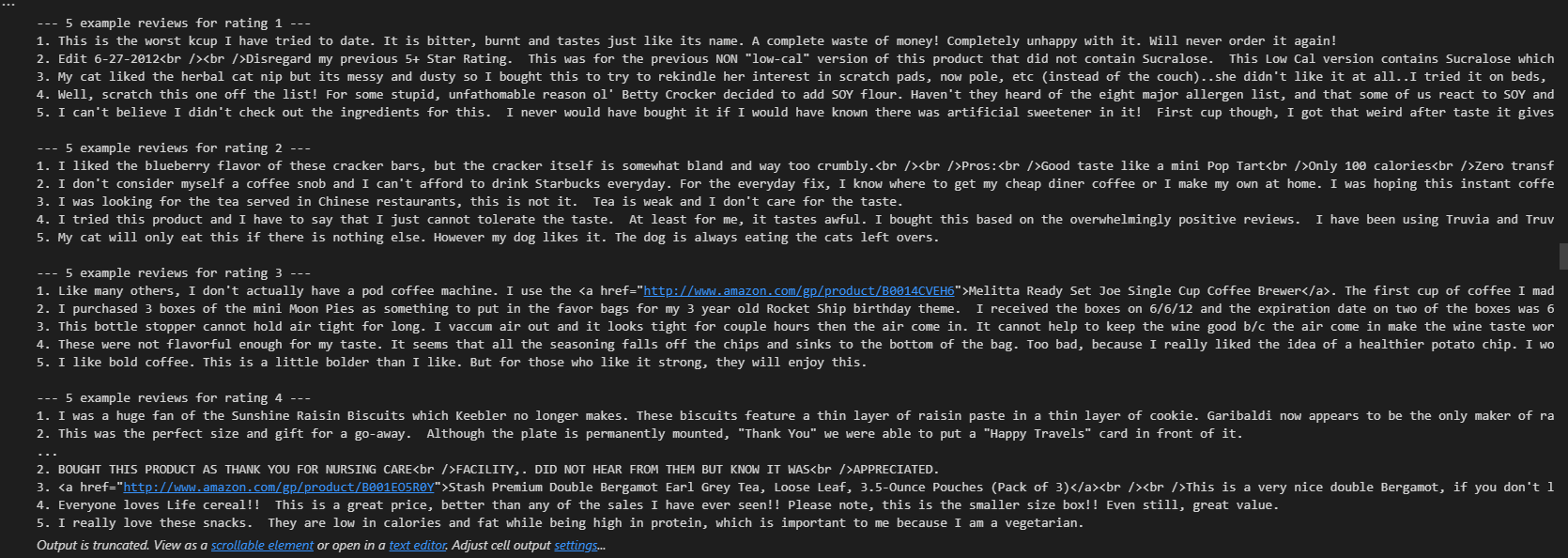
**5 Example Reviews per Rating**

for rating in sorted(df['Score'].unique()):

print(f"\n--- 5 sample reviews for rating {rating} ---")

for review in df[df['Score'] == rating]['review\_text'].sample(5, random\_state=42):

print('-', review)



**Imbalanced & Balanced Dataset Creation**

Imbalanced Dataset

total\_samples = 2000

target = {1: 0.10, 2: 0.15, 3: 0.20, 4: 0.25, 5: 0.30}

samples\_per\_class = {star: int(total\_samples \* pct) for star, pct in target.items()}

dfs = []

for star, n in samples\_per\_class.items():

grp = df[df['Score'] == star]

dfs.append(grp.sample(n=n, random\_state=42, replace=len(grp) < n))

imbalanced = pd.concat(dfs).sample(frac=1, random\_state=42)

imbalanced.to\_csv('data/cleaned\_dataset/imbalanced\_data.csv', index=False)

**Balanced Dataset**

min\_n = df['Score'].value\_counts().min()

balanced = df.groupby('Score').sample(n=min\_n, random\_state=42)

balanced.to\_csv('data/cleaned\_dataset/balanced\_data.csv', index=False)

**Stopwords Removal**

import pandas as pd

file\_path = r'D:\Projects\automated-review-rating-system\data\cleaned\_dataset\imbalanced\_data.csv'

df = pd.read\_csv(r'D:\Projects\automated-review-rating-system\data\cleaned\_dataset\imbalanced\_data.csv')

from collections import Counter

import itertools

import nltk

nltk.download('stopwords')

from nltk.corpus import stopwords

stop\_words = set(stopwords.words('english'))

def get\_top\_words(texts, n=10):

all\_words = list(itertools.chain(\*[t.split() for t in texts]))

filtered\_words = [w for w in all\_words if w not in stop\_words]

return Counter(filtered\_words).most\_common(n)

def get\_removed\_stopwords(texts):

all\_words = list(itertools.chain(\*[t.split() for t in texts]))

removed\_words = [w for w in all\_words if w in stop\_words]

return Counter(removed\_words).most\_common()

# Top 10 words for each rating

for rating in sorted(df['Score'].unique()):

texts = df[df['Score'] == rating]['Text']

print(f"Top words for rating {rating}:")

print(get\_top\_words(texts, n=10))

print()

print(f"All removed stopwords for rating {rating}:")

removed\_sw = get\_removed\_stopwords(texts)

# optionally print top N removed stopwords, e.g., top 20

print(removed\_sw[:20])

print()



**Top words for rating 1:**

[('I', 521), ('/><br', 153), ('like', 86), ('The', 75), ('one', 58), ('product', 56), ('This', 56), ('would', 55), ('taste', 53), ('-', 47)]

**All removed stop words for rating 1:**

[('the', 720), ('and', 436), ('to', 413), ('a', 367), ('of', 324), ('it', 226), ('is', 215), ('this', 205), ('was', 197), ('that', 191), ('in', 185), ('for', 158), ('not', 136), ('my', 129), ('have', 127), ('with', 117), ('but', 114), ('are', 110), ('on', 103), ('they', 101)]

**Top words for rating 2:**

[('I', 940), ('like', 176), ('/><br', 162), ('The', 125), ('would', 118), ('It', 104), ('taste', 102), ('coffee', 94), ('product', 89), ('one', 86)]

**All removed stop words for rating 2:**

[('the', 1100), ('a', 696), ('and', 638), ('to', 636), ('of', 495), ('it', 399), ('is', 393), ('this', 333), ('in', 287), ('not', 285), ('was', 277), ('that', 269), ('but', 257), ('for', 251), ('have', 195), ('my', 194), ('with', 191), ('are', 170), ('you', 164), ('as', 155)]

**Top words for rating 3:**

[('I', 1590), ('/><br', 316), ('like', 297), ('The', 220), ('would', 209), ('taste', 181), ('It', 155), ('good', 142), ('one', 131), ('product', 130)]

**All removed stop words for rating 3:**

[('the', 2129), ('a', 1332), ('and', 1133), ('to', 1031), ('of', 943), ('it', 769), ('is', 727), ('this', 561), ('in', 535), ('that', 520), ('but', 512), ('for', 497), ('not', 444), ('was', 425), ('with', 393), ('have', 354), ('my', 337), ('you', 310), ('are', 290), ('as', 272)]

**Top words for rating 4:**

[('I', 1699), ('/><br', 372), ('like', 342), ('The', 258), ('good', 235), ('one', 180), ('coffee', 171), ('taste', 161), ('It', 158), ('would', 151)]

**All removed stopwords for rating 4:**

[('the', 2055), ('a', 1589), ('and', 1385), ('to', 1223), ('of', 1037), ('is', 954), ('it', 853), ('for', 643), ('in', 593), ('this', 569), ('that', 563), ('but', 493), ('with', 433), ('not', 391), ('are', 387), ('my', 385), ('have', 367), ('was', 361), ('as', 345), ('you', 328)]

**Top words for rating 5:**

[('I', 841), ('/><br', 139), ('love', 122), ('like', 121), ('The', 107), ('great', 101), ('one', 98), ('It', 95), ('This', 90), ('good', 76)]

**All removed stopwords for rating 5:**

[('the', 913), ('and', 838), ('a', 675), ('to', 573), ('is', 465), ('of', 464), ('it', 390), ('for', 347), ('this', 330), ('in', 314), ('that', 221), ('are', 216), ('have', 213), ('with', 213), ('my', 204), ('you', 195), ('on', 168), ('but', 168), ('as', 154), ('so', 151)]

**Lemmatization**

def lemmatize\_text(text):

"""

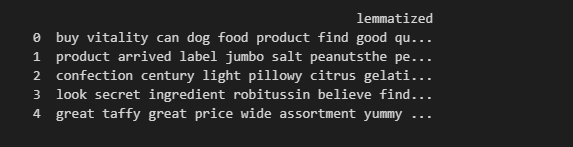
Lemmatize text using SpaCy and remove stopwords.

"""

doc = nlp(str(text))

tokens = [token.lemma\_ for token in doc if not token.is\_stop and token.is\_alpha]

return ' '.join(tokens)



**Filtering reviews (Less than 3 words or excessive words)**

def filter\_reviews(df, text\_column='lemmatized', min\_words=3, max\_words=200):

"""

Filters the DataFrame to keep only rows where the `text\_column` has

at least `min\_words` and at most `max\_words` words.

"""

df['word\_count'] = df[text\_column].apply(lambda x: len(str(x).split()))

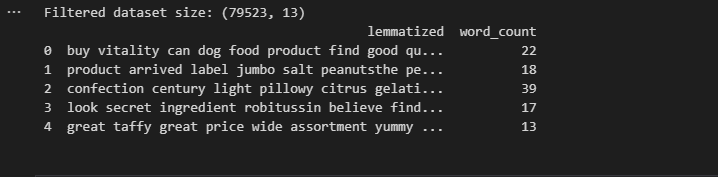
filtered\_df = df[(df['word\_count'] >= min\_words) & (df['word\_count'] <= max\_words)].reset\_index(drop=True)

return filtered\_df

filtered\_df = filter\_reviews(df, text\_column='lemmatized', min\_words=3, max\_words=200)

print(f"Filtered dataset size: {filtered\_df.shape}")

print(filtered\_df[[ 'lemmatized', 'word\_count']].head())



**Data Cleaning - Removing URLs, Tags, Emojis, Punctuation, Special Characters**

import pandas as pd

import os

import re

def clean\_text(text):

"""

Remove URLs, HTML tags, emojis, punctuation, and special characters from text.

"""

text = str(text).lower() # Lowercase

text = re.sub(r'http\S+|www.\S+', '', text) # Remove URLs

text = re.sub(r'<.\*?>', '', text) # Remove HTML tags

text = re.sub(r'[^\w\s]', '', text) # Remove emojis, punctuation, special chars

text = re.sub(r'\s+', ' ', text).strip() # Remove extra whitespace

return text

folder\_path = r"D:\Projects\automated-review-rating-system\data\Day3 Data"

df\_list = []

for filename in os.listdir(folder\_path):

if filename.endswith('.csv'):

filepath = os.path.join(folder\_path, filename)

df\_temp = pd.read\_csv(filepath)

if 'Text' in df\_temp.columns:

df\_temp['clean\_text'] = df\_temp['Text'].apply(clean\_text)

df\_list.append(df\_temp)

else:

print(f"Warning: 'Text' column missing in {filename}")

# Combine all cleaned DataFrames

df\_all\_cleaned = pd.concat(df\_list, ignore\_index=True)

print(f"Combined dataset size after cleaning: {df\_all\_cleaned.shape}")

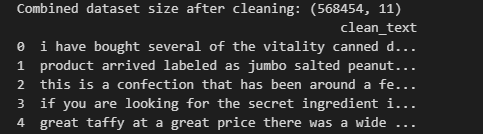
print(df\_all\_cleaned[['clean\_text']].head())

# Saving cleaned DataFrame to a CSV file

output\_path = r"D:\Projects\automated-review-rating-system\data\Day3 Data\cleaned\_reviews.csv"

df\_all\_cleaned.to\_csv(output\_path, index=False)

print(f"Cleaned data saved to { automated-review-rating-system\data\cleaned\_dataset\cleaned\_dataset.csv}")



**Data Visualization : Bar chart for review count per rating**

import matplotlib.pyplot as plt

import seaborn as sns

plt.figure(figsize=(8,5))

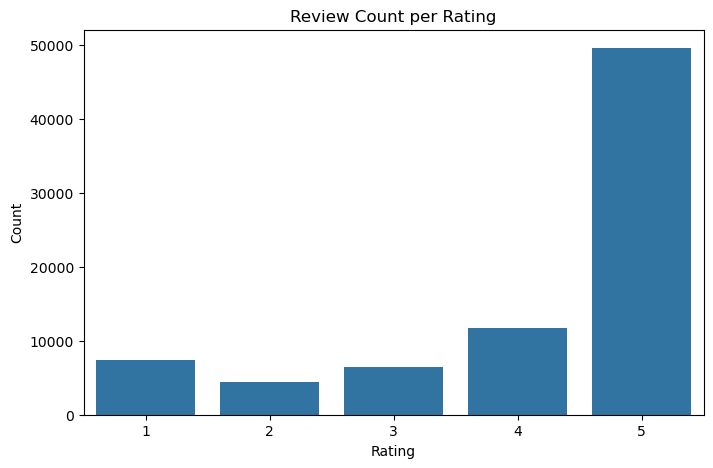
sns.countplot(x='Score', data=filtered\_df)

plt.title('Review Count per Rating')

plt.xlabel('Rating')

plt.ylabel('Count')

plt.show()



**Boxplot for word count distribution by rating**

plt.figure(figsize=(8,5))

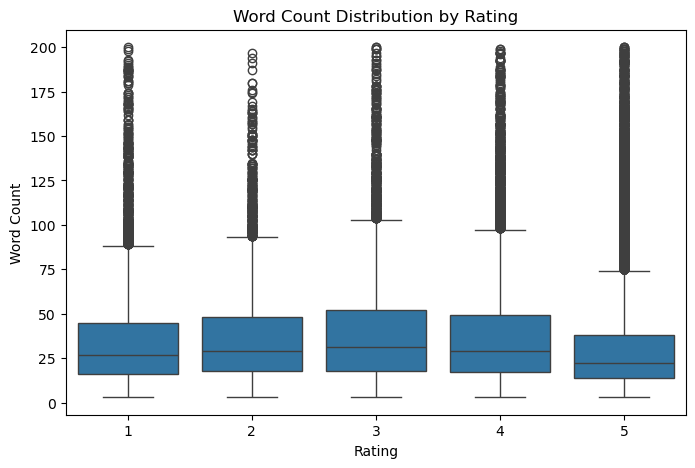
sns.boxplot(x='Score', y='word\_count', data=filtered\_df)

plt.title('Word Count Distribution by Rating')

plt.xlabel('Rating')

plt.ylabel('Word Count')

plt.show()



**Displaying sample reviews for each rating**

for Score in sorted(filtered\_df['Score'].unique()):

print(f"\n--- {Score} Star Reviews ---")

samples = filtered\_df[filtered\_df['Score']==Score]['Text'].head(3)

for review in samples:

print(review)

**Creating a balanced dataset : Sample equal number of reviews from each rating class to balance the dataset**

import pandas as pd

# Use your processed DataFrame, e.g., filtered\_df

# Set desired sample count per class

samples\_per\_class = 2000

# Sample equal number from each rating (with or without replacement as needed)

balanced\_df = filtered\_df.groupby('Score').apply(

lambda x: x.sample(n=samples\_per\_class, random\_state=42)

if len(x) >= samples\_per\_class else x.sample(n=samples\_per\_class, replace=True, random\_state=42)

)

# Remove multi-index from groupby

balanced\_df = balanced\_df.reset\_index(drop=True)

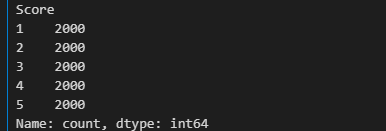
# Check balance

print(balanced\_df['Score'].value\_counts().sort\_index())

output\_path = r"D:\Projects\automated-review-rating-system\data\Day3 Data\balanced\_reviews.csv"

balanced\_df.to\_csv(output\_path, index=False)

print(f"Balanced dataset saved to {output\_path}")



**Train Test split for balanced dataset**

import pandas as pd

from sklearn.model\_selection import train\_test\_split

from sklearn.feature\_extraction.text import TfidfVectorizer

# Load the balanced dataset

file\_path = r"D:\Projects\automated-review-rating-system\data\Day3 Data\balanced\_reviews.csv"

balanced\_df = pd.read\_csv(file\_path)

# Separate features and target

X = balanced\_df['clean\_text'] # replace if using another text column like 'lemmatized'

y = balanced\_df['Score']

# Stratified train-test split, 80% train, 20% test

X\_train, X\_test, y\_train, y\_test = train\_test\_split(

X, y, test\_size=0.2, stratify=y, random\_state=42, shuffle=True)

print(f"Train set size: {len(X\_train)}, Test set size: {len(X\_test)}")

print(f"Train class distribution:\n{y\_train.value\_counts()}")

print(f"Test class distribution:\n{y\_test.value\_counts()}")

# TF-IDF Vectorization: fit on train, transform on both sets

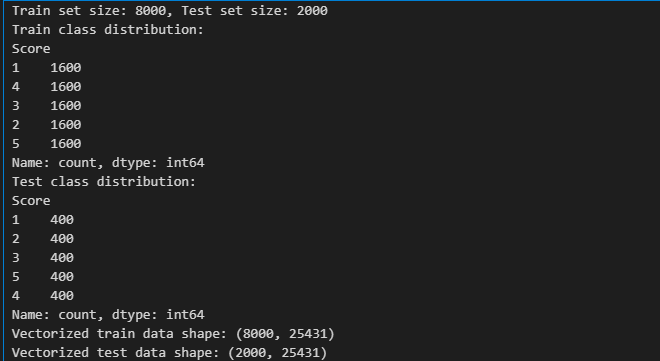
vectorizer = TfidfVectorizer()

X\_train\_vec = vectorizer.fit\_transform(X\_train)

X\_test\_vec = vectorizer.transform(X\_test)

print(f"Vectorized train data shape: {X\_train\_vec.shape}")

print(f"Vectorized test data shape: {X\_test\_vec.shape}")



**Train Test Split for imbalanced data**

from sklearn.model\_selection import train\_test\_split

X = df['lemmatized']

y = df['Score']

X\_train, X\_test, y\_train, y\_test = train\_test\_split(

X, y, test\_size=0.2, stratify=y, random\_state=42, shuffle=True

)

print("Train and test sizes:", len(X\_train), len(X\_test))

print("Train class distribution:\n", y\_train.value\_counts())

print("Test class distribution:\n", y\_test.value\_counts())

#Vectorization

from sklearn.feature\_extraction.text import TfidfVectorizer

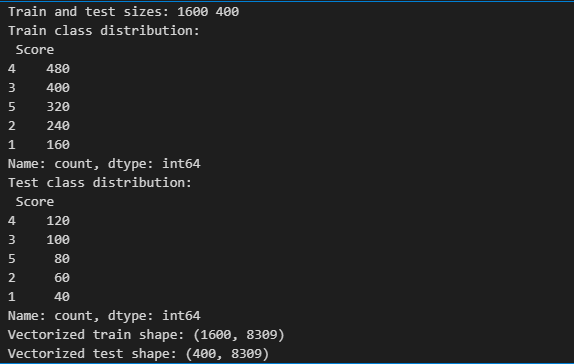
vectorizer = TfidfVectorizer()

X\_train\_vec = vectorizer.fit\_transform(X\_train) # Fit only on train!

X\_test\_vec = vectorizer.transform(X\_test)

print("Vectorized train shape:", X\_train\_vec.shape)

print("Vectorized test shape:", X\_test\_vec.shape)



**Algorithm Deep Dive Documentation: Logistic Regression**

**A. Algorithm Type & Objective**

Type: Linear, supervised classification (can also be used for regression, but here for text classification).

Objective: Directly predicts the probability that an input text belongs to each possible class (e.g., a sentiment rating), using a logistic (“sigmoid” or “softmax” in multiclass) function.

**B. How the Algorithm Works (Mathematical Intuition)**

**Features**: Each document is represented as a vector (e.g., TF-IDF features from vectorization).

**Linear combination**: Calculates a weighted sum of these features, plus a bias term**.**

**Logistic function:**Applies a sigmoid (binary case) or softmax (multiclass) to output a probability for each class.

**Training:**Finds the optimal set of weights that minimize the difference between predicted and actual labels (via cross-entropy/log-loss).

**Decision boundary**: Finds the “best” linear separation between classes in the high-dimensional feature space.

**Mathematics:**

**p(y=1∣x)=σ(w⋅x+b)=11+e−(w⋅x+b)p(y=1∣x)=σ(w⋅x+b)=1+e−(w⋅x+b)1**

Where σσ is the sigmoid, ⋅⋅ is the dot product, and ww, bb are learned.

**C. Key Hyper parameters**

• Inverse regularization strength (C=1/lambda). Lower values mean stronger regularization (simpler model), higher values allow a better fit (risking overfit).

Default: 1.0. Tune over log-scale, e.g., [0.01, 0.1, 1, 10, 100].

• **Penalty**: Type of regularization, e.g., 'l2' (default, recommended), or 'l1' (can enforce sparsity).

• **Solver**: Optimization algorithm. 'liblinear' (good for small datasets and L1), 'lbfgs' (default, fits multiclass well).

• **max\_iter**: Maximum solver iterations. Increase if convergence warnings arise.

• **class\_weight**: Handle class imbalance ('balanced' sets weights automatically).

**Strengths & Limitations (for Text Classification)**

**Strengths:**

Simple, interpretable, and fast to train—even with many features.

Handles large, sparse feature sets elegantly (ideal for bag-of-words, TF-IDF, one-hot).

Outputs well-calibrated probabilities.

Robust to correlated features (with regularization).

**Limitations:**

Assumes linear separability—may underperform with complex, nonlinear phenomena.

Each feature (word/ngram) contributes linearly; cannot capture word sequences or non-obvious feature interactions as well as tree-based or neural models.

Sensitive to outliers and collinearity if regularization is not used.

**When to Use / When Not to Use**

Use When:

You want a strong baseline for text classification.

Datasets are medium to large, features are high-dimensional and sparse.

Fast training and model transparency are important.

Multi-class or multi-label problems with interpretable weights.

Avoid When:

Underlying relationships are highly nonlinear or need sequence/context modelling.

You need to capture subtle patterns or word order (consider RNNs, CNNs, transformers for these).

Data is extremely imbalanced and cannot be rectified through sampling/weighting.

**Logistic Regression Model Training and Evaluation**

* Model Used: Logistic Regression from scikit-learn.
* Training: The model is trained (fit) on the TF-IDF vectorized training dataset (X\_train\_vec) with their actual labels (y\_train). This lets the model learn the relationship between text features and review ratings.
* Prediction: The trained model predicts ratings on the test TF-IDF vectors (X\_test\_vec).

Evaluation Metrics:

* Accuracy: Measures the percentage of correctly predicted ratings over the test dataset.
* Classification Report: Shows precision, recall, and F1-score for each rating class, providing detailed insight into the model’s performance per class.
* Confusion Matrix: A table showing the distribution of actual vs predicted ratings, highlighting the types of errors the model makes.

By using these metrics, we assess how well the Logistic Regression model generalizes to unseen data and identify areas where it may misclassify ratings.

**Balanced Dataset Model Training and Evaluation Documentation**

**1. Algorithm Used**:

* Logistic Regression was chosen as the primary model because:
* It provides a strong, interpretable baseline especially suited for text classification with TF-IDF features.
* It efficiently handles high-dimensional, sparse data.
* It outputs probabilistic predictions allowing detailed evaluation.

**2. Data Preprocessing Steps:**

* Data Loading: Loaded balanced dataset from CSV containing review texts and associated ratings.
* Text Cleaning: Converted text to lowercase, removed URLs, HTML tags, emojis, non-ASCII characters, punctuation, digits, and extra whitespace.
* Lemmatization: Applied spaCy’s English language model to convert words to their base forms, removed stopwords, non-alphabetic tokens, and tokens shorter than 2 characters, resulting in normalized and meaningful textual input.

import spacy

import re

nlp = spacy.load('en\_core\_web\_sm')

nlp = spacy.load('en\_core\_web\_sm')

def clean\_text(text):

"""

Lowercase, remove URLs, HTML tags, emojis, punctuation, non-ASCII, digits, extra whitespace.

"""

text = str(text).lower()

text = re.sub(r'http\S+|www.\S+', '', text)

text = re.sub(r'<.\*?>', '', text)

text = re.sub(r'[^\x00-\x7F]+', ' ', text) # Remove emojis/unicode

text = re.sub(r'[^\w\s]', '', text) # Remove punctuation

text = re.sub(r'\d+', '', text) # Remove digits

text = re.sub(r'\s+', ' ', text).strip()

return text

def lemmatize\_text(text):

"""

Lemmatize using spaCy, remove stopwords, keep alphabetic tokens longer than 1 character.

"""

doc = nlp(text)

tokens = [token.lemma\_ for token in doc if not token.is\_stop and token.is\_alpha and len(token.lemma\_) > 1]

return ' '.join(tokens)

df\_bal['clean\_text'] = df\_bal['Text'].apply(clean\_text)

df\_bal['lemmatized'] = df\_bal['clean\_text'].apply(lemmatize\_text)

print(df\_bal[['Text', 'clean\_text', 'lemmatized']].head())

**3. Data Splitting:**

* Used stratified train-test split (80% training, 20% testing), preserving class distribution to ensure fair evaluation.

X = df\_bal['lemmatized'] # Using lemmatized column

y = df\_bal['Score']

X\_train, X\_test, y\_train, y\_test = train\_test\_split(

X, y, test\_size=0.2, stratify=y, random\_state=42, shuffle=True

)

print("Train distribution:\n", y\_train.value\_counts())

print("Test distribution:\n", y\_test.value\_counts())

**4. Feature Extraction:**

* Converted the lemmatized text into numerical features using TF-IDF vectorization, capturing the importance of words and phrases within and across reviews.

from sklearn.feature\_extraction.text import TfidfVectorizer

from sklearn.model\_selection import train\_test\_split

tfidf = TfidfVectorizer()

X\_train\_vec = tfidf.fit\_transform(X\_train)

X\_test\_vec = tfidf.transform(X\_test)

print("TF-IDF train shape:", X\_train\_vec.shape)

print("TF-IDF test shape:", X\_test\_vec.shape)

**5. Model Training:**

* Trained Logistic Regression with a maximum iteration limit set for convergence.
* Regularization helped prevent overfitting on high-dimensional input.

from sklearn.linear\_model import LogisticRegression

from sklearn.metrics import accuracy\_score, classification\_report, confusion\_matrix

clf = LogisticRegression(max\_iter=1000, random\_state=42)

clf.fit(X\_train\_vec, y\_train)

y\_pred = clf.predict(X\_test\_vec)

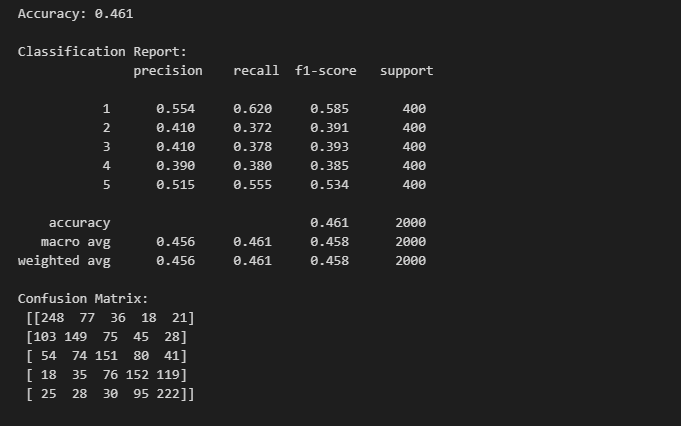
print("Accuracy:", accuracy\_score(y\_test, y\_pred))

print("\nClassification Report:\n", classification\_report(y\_test, y\_pred, digits=3))

print("Confusion Matrix:\n", confusion\_matrix(y\_test, y\_pred))

**6. Model Evaluation:**

* Calculated and analysed the following metrics on the test set:
  + Accuracy: Overall percent of correctly predicted ratings.
  + Precision, Recall, F1-score (per class): Showed how well the model balances the detection of each rating class.
  + Confusion Matrix: Revealed details of which ratings were confused with each other, noting common misclassifications between adjacent ratings, typical in ordinal data.



**7. Insights:**

* Logistic Regression and Random Forest performed well as a baseline with balanced data.
* The model showed strongest performance on extreme classes (lowest and highest ratings), with moderate challenges on middle ratings.
* Cleaned and lemmatized text, combined with TF-IDF features, gave the model meaningful input for learning.
* Stratified splitting ensured realistic evaluation on unseen data.

**8. Summary:**

* The pipeline—from cleaning, lemmatization, feature extraction, model training, to detailed evaluation—provided a reproducible and interpretable workflow to classify balanced review rating data. The comprehensive metrics allowed understanding of strengths and weaknesses in model accuracy and class-level prediction quality.

**Imbalanced Dataset Model Training and Evaluation Documentation**

**1.Data Preparation and Preprocessing**

Data Loading:

* + Imported the imbalanced dataset from CSV (imbalanced\_data.csv) containing:
  + Text— the customer’s review.
  + Score — the label (target class, e.g., ratings 1–5).

Text Cleaning: Applied a cleaning function to:

* + Convert text to lowercase.
  + Remove URLs, HTML tags, emojis, punctuation, digits, and extra whitespace.

Lemmatization:

* + Used spaCy to convert words to their base form.
  + Removed stopwords, non‑alphabetic tokens, and very short tokens.

**2. Train-Test Splitting**

* + Split data into 80% training and 20% testing while stratifying (stratify=y) so that the distribution of ratings in both sets matched the original imbalance.

from sklearn.model\_selection import train\_test\_split

# y is your target, e.g. 'Score'

X = df

y = df['Score']

X\_train, X\_test, y\_train, y\_test = train\_test\_split(

X, y, test\_size=0.2, stratify=y, random\_state=42

)

**3. Feature Extraction**

* + Used TF-IDF Vectorization to convert lemmatized text into numerical feature vectors.
  + Captured word importance relative to:
    - The review it appears in.
    - The whole dataset (to down-weight common words and up-weight unique, informative ones).

**4. Handling Class Imbalance**

* + Applied two approaches depending on the experiment:
  + Class weight='balanced' in classifiers — automatically gives more importance to minority classes.
  + **SMOTE** (Synthetic Minority Over-sampling Technique) in some runs — Created synthetic training samples for minority classes so the training set became balanced.

from imblearn.pipeline import Pipeline as ImbPipeline

from imblearn.over\_sampling import SMOTE

pipeline = ImbPipeline([

('preprocessor', preprocessor),

('smote', SMOTE(random\_state=42)),

('clf', LogisticRegression(max\_iter=1000, class\_weight='balanced', random\_state=42))

])

**5. Algorithms Used**

Tried multiple classifiers to see which works best on the imbalanced dataset:

* + Logistic Regression
    - Linear, interpretable, often works well with TF-IDF features.
    - Used class\_weight='balanced' and hyperparameter tuning for C, penalty, solver, and TF-IDF settings.
  + Random Forest
    - An ensemble of decision trees.
    - Tuned parameters like number of trees (n\_estimators), depth, features per split, etc.
  + SVM (LinearSVC)
    - Strong for high-dimensional text data.
    - Tuned parameters: C (regularisation) and type of loss function, with class\_weight='balanced'.

**6. Hyperparameter Tuning**

Used GridSearchCV or RandomizedSearchCV with 5-fold cross-validation and f1\_weighted scoring:

F1-weighted accounts for class imbalance by weighting each class’s F1-score by its support.

Tuned:

**TF-IDF vectorizer** parameters: ngram\_range, max\_df, min\_df, stop\_words, max\_features.

Model parameters specific to each algorithm.

from sklearn.linear\_model import LogisticRegression

from sklearn.model\_selection import GridSearchCV

param\_grid = {

'preprocessor\_\_text\_\_max\_df': [0.7, 1.0],

'preprocessor\_\_text\_\_min\_df': [1, 5],

'clf\_\_C': [0.01, 0.1, 1, 10],

'clf\_\_penalty': ['l2'],

'clf\_\_solver': ['lbfgs']

}

grid = GridSearchCV(

estimator=pipeline,

param\_grid=param\_grid,

cv=5,

scoring='f1\_weighted',

n\_jobs=-1,

verbose=2

)

grid.fit(X\_train, y\_train)

**7. Model Evaluation**

For each model, evaluated on the held-out test set using:

* Accuracy — Overall proportion of correct predictions.
* Classification Report:
  + Precision — Of items predicted as a class, how many were correct.
  + Recall — Of items actually belonging to a class, how many were found.
  + F1-score — Harmonic mean of precision and recall, per class.
  + Weighted and macro averages.
* Confusion Matrix — Detailed breakdown of true vs predicted classes, showing which ratings get confused.

from sklearn.metrics import classification\_report, roc\_auc\_score

from sklearn.preprocessing import label\_binarize

best\_model = grid.best\_estimator\_ # or rf\_grid.best\_estimator\_ for Random Forest

y\_pred = best\_model.predict(X\_test)

print(classification\_report(y\_test, y\_pred))

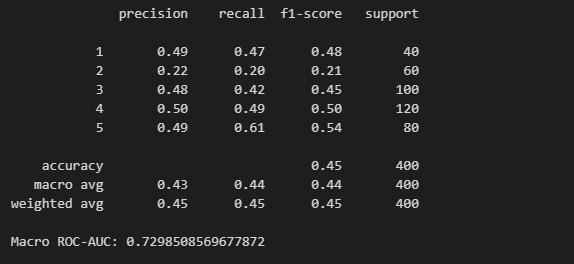
# For multiclass ROC AUC

y\_test\_bin = label\_binarize(y\_test, classes=sorted(y.unique()))

y\_prob = best\_model.predict\_proba(X\_test)

roc\_auc = roc\_auc\_score(y\_test\_bin, y\_prob, average='macro', multi\_class='ovr')

print('Macro ROC-AUC:', roc\_auc)



**8. Findings / Insights**

* Models performed best on classes with more samples (majority classes).
* Despite balancing methods, predicting mid-range ratings (e.g., 2–4) remained harder due to overlapping textual features.
* SMOTE + tuned parameters improved recall for minority classes but sometimes reduced precision slightly.
* Random Forest and Logistic Regression with bigram TF-IDF and balancing generally gave the best trade-off between precision and recall.

**9. Summary Workflow**

* + Load & Inspect the imbalanced data.
  + Clean & Lemmatize text (remove noise, normalise words).
  + Split into training and testing (stratified).
  + Vectorise text with TF-IDF.
  + Handle imbalance via class\_weight or SMOTE.
  + Train different classifiers with hyperparameter tuning.
  + Evaluate with accuracy, detailed class metrics, and confusion matrix.
  + Select the model that gives the best balanced performance — not just highest accuracy

**Saving and Using Saved Models**

**1. Saving Model A (Balanced Dataset)**

* Trained and tuned the Logistic Regression model on the balanced dataset and used TF-IDF vectorization
  + The trained model (best\_model)
  + The TF-IDF vectorizer (vectorizer) used to convert text to numeric features
* This step is essential since the model alone can’t process raw text without the vectorizer.

import joblib

# Save the balanced model

joblib.dump(best\_model, 'model\_A\_balanced.pkl')

# Save the TF-IDF vectorizer for balanced model

joblib.dump(vectorizer, 'vectorizer\_model\_A.pkl')

print("✅ Model A and vectorizer saved successfully.")

**2. Saving Model B (Imbalanced Dataset)**

* Imbalanced dataset model as a full preprocessing and training pipeline (with text vectorization, numeric scaling, SMOTE balancing, and Logistic Regression) using imblearn.pipeline.Pipeline, you can save the entire pipeline:

import joblib

# Save the full imbalanced model pipeline

joblib.dump(pipeline, 'model\_B\_imbalanced\_pipeline.pkl')

print("✅ Imbalanced model pipeline saved successfully.")

* Saving the entire pipeline ensures that all preprocessing steps and model parameters are preserved, so you can use the model seamlessly later.

**Cross-Testing**

Evaluate how well each model generalizes to data distributions different from those it was trained on.

**Steps:**

**Test Model\_A on imbalanced data:**

Load imbalanced lemmatized data, use trained vectorizer\_A/model\_A for inference and evaluation.

**Test Model\_B on balanced data:**

Load balanced lemmatized data, use trained vectorizer\_B/model\_B.

**Key Point:**

Always load and use the matching vectorizer and model together to avoid feature count mismatches.

**Evaluation Metrics:**

* + Classification report (precision, recall, F1)
  + Confusion matrix
  + Accuracy

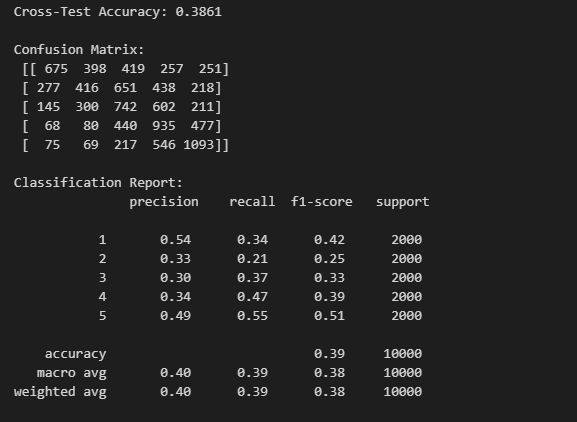
from sklearn.metrics import classification\_report, confusion\_matrix, accuracy\_score

y\_cross\_pred = model.predict(X\_cross\_vec)

print("Cross-Test Accuracy:", accuracy\_score(y\_cross, y\_cross\_pred))

print("\nConfusion Matrix:\n", confusion\_matrix(y\_cross, y\_cross\_pred))

print("\nClassification Report:\n", classification\_report(y\_cross, y\_cross\_pred))



**Deep Learning Research**

**Why Deep Learning for Text Classification?**

Deep learning models (e.g., neural networks) automatically learn feature representations, capturing complex patterns in text that can be missed by traditional ML (like Logistic Regression), especially on large, nuanced datasets.

**When does deep learning outperform ML?**

* Large datasets, complex language use (context, sarcasm, etc.)
* Need for end-to-end feature learning (no manual feature engineering)
* Better handling of long-range word dependencies (with LSTM/Transformer)

**Deep Learning Model Implementation**

* Keras Sequential model:
* Tokenizer/fitted on lemmatized text
* Embedding layer + pooling + dense layers + softmax
* Trained and validated using the same split as ML models.
* Saved with:
  + model.save("deep\_model\_balanced.h5")
  + pickle.dump(tokenizer, ...)
  + json.dump(label\_to\_int, ...)
* Sanity tested: Load model and tokenizer, predict on a sample review, confirm correct output.

**Streamlit Interface**

**Design Decisions**

* Single text area for input.
* Button for prediction.
* Side-by-side prediction display so users immediately see differences.
* Expandable info box explaining the models for transparency.
* Modular code – Easy to add/remove models and UI features.

**Example User Flow**

1. User enters review text.
2. Clicks “Get Predictions.”
3. App displays:

* Model\_A (balanced) predicted score
* Model\_B (imbalanced) predicted score
* Deep model predicted score

**Insights & Recommendations**

* Imbalanced models may over-predict frequent classes; balancing helps generalization.
* Deep models likely outperform traditional ML if enough data and compute are available, or if context and semantics matter a lot.
* Clear UI lets users appreciate model differences and builds trust through transparency.