AUTOMATED RATING REVIEW SYSTEM

Imbalanced Dataset Creation

1.PROJECT OVERVIEW

This project predicts customer review ratings based on textual feedback. It involves cleaning and preprocessing review text and creating an imbalanced dataset by using the remaining reviews not included in the balanced dataset. The dataset is transformed into TF-IDF features, and a stratified train-test split is applied to maintain realistic class distribution. The system helps analyze model performance on skewed data, providing insights into review patterns, customer sentiment, and how models handle imbalanced classes

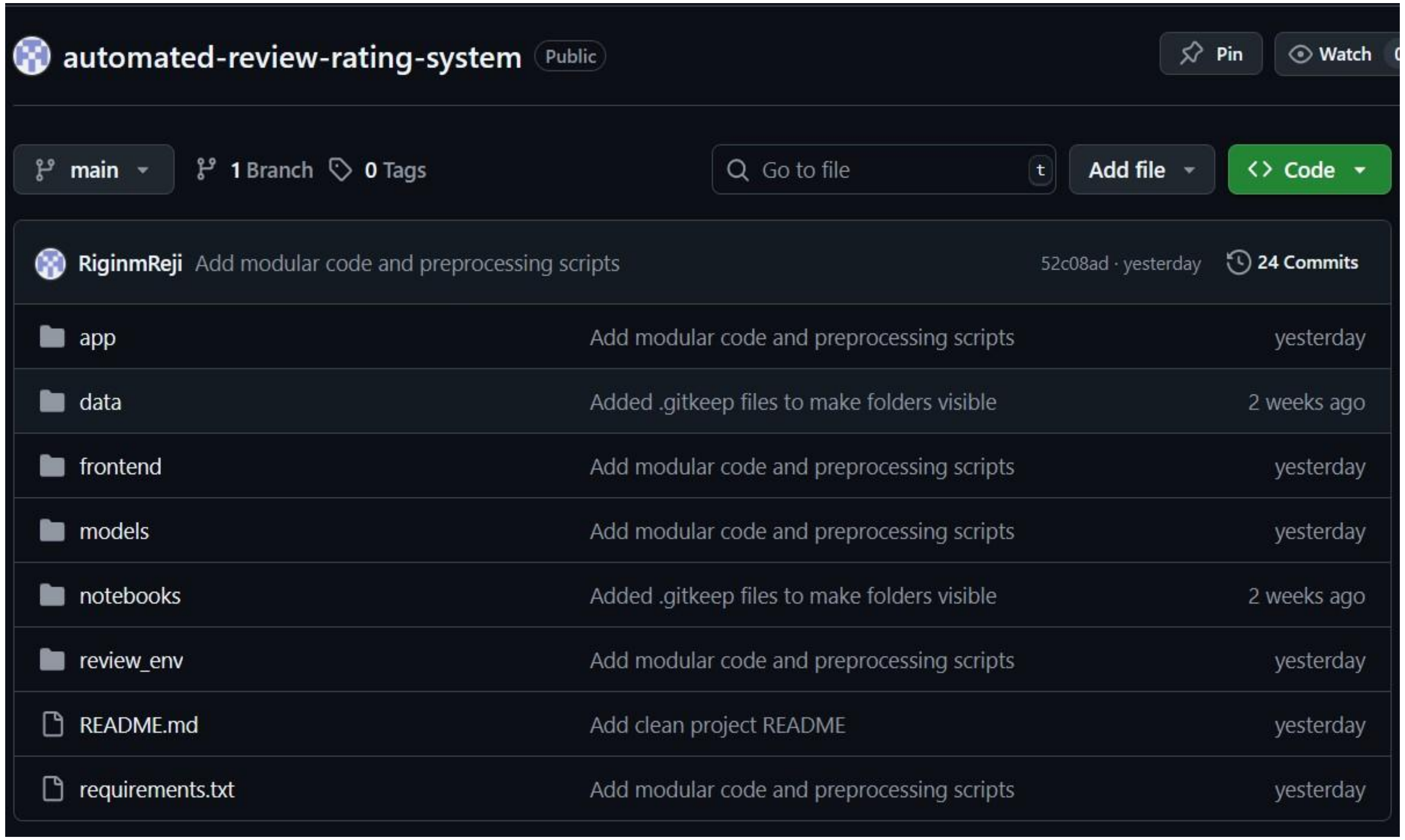
2. ENVIRONMENTAL SETUP

- Python: 3.9+
- Libraries: pandas, numpy, nltk, scikit-learn, re
- NLTK Resources: stopwords, punkt, wordnet
- IDE: Google Colab and VS Code
- Hardware: Laptop

3.GITHUB PROJECT SETUP

Created GitHub repository : **automated-review-rating-system**

Structure of directory



automated-review-rating-system Public

RiginmReji Add modular code and preprocessing scripts 52c08ad · yesterday 24 Commits

app	Add modular code and preprocessing scripts	yesterday
data	Added .gitkeep files to make folders visible	2 weeks ago
frontend	Add modular code and preprocessing scripts	yesterday
models	Add modular code and preprocessing scripts	yesterday
notebooks	Added .gitkeep files to make folders visible	2 weeks ago
review_env	Add modular code and preprocessing scripts	yesterday
README.md	Add clean project README	yesterday
requirements.txt	Add modular code and preprocessing scripts	yesterday

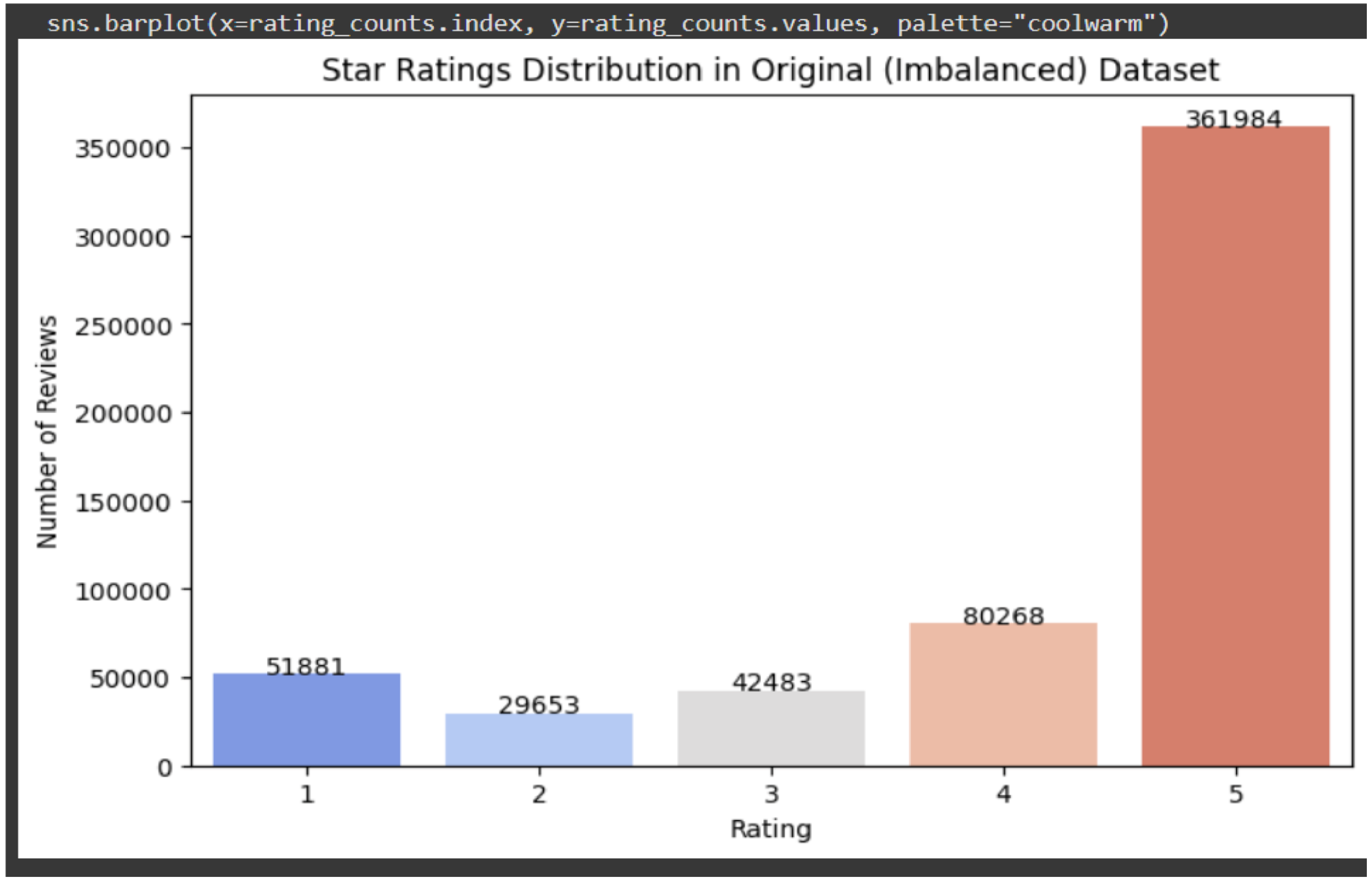
4.DATA COLLECTION

- The dataset was collected from Kaggle, containing real-world customer reviews from e-commerce platforms.
- It has 542454 rows and 14 columns
- Dataset link = https://www.kaggle.com/snap/amazon-fine-food-reviews/downloads/amazon-fine-food-reviews.zip
- It includes the review text and corresponding star ratings (1–5), along with optional metadata such as product IDs and timestamps
- Initial preprocessing involved removing duplicates, handling missing values, and filtering extremely short or long reviews to ensure quality for analysis and modeling.
- Final dataset contains 2 columns with Rating and Review_text
- 1 star -33,308, 2 star - 17,804, 3 star – 26,713, 4 star - 53,068, 5 star - 247801

4.2.2 Imbalanced dataset

Link for imbalanced dataset =

- Imbalanced dataset was created with 1 star – 10%, 2 star – 15%, 3 star – 15%, 4 star – 30% , 5 star – 20%



```
sns.barplot(x=rating_counts.index, y=rating_counts.values, palette="coolwarm")
```

5.DATA PREPROCESSING

Effective data preprocessing is essential to improve the performance and reliability of machine learning models, especially when dealing with imbalanced data. The following techniques were applied to prepare the remaining review dataset (not included in the balanced set) for modeling.

5.1. Removing duplicates

Duplicate rows containing the exact same review and rating were removed from the remaining data to prevent bias and overfitting. This ensured that the **imbalanced dataset** only includes unique observations not present in the balanced dataset.

Code:

```
before = imbalanced_df.shape[0]
imbalanced_df = imbalanced_df.drop_duplicates(subset=['Review_text'])
after = imbalanced_df.shape[0]

print(f"Removed {before - after} duplicate reviews from the imbalanced dataset.")
print(f"Remaining reviews: {after}")
```

5.2. Removing conflicting reviews

Some reviews in the remaining data had identical text but different star ratings. These inconsistencies could confuse the model. Such conflicting entries were identified and removed to maintain **label clarity** in the imbalanced dataset.

Code:

```
conflicts = imbalanced_df.groupby("Review_text")["Rating"].nunique()
conflicting_reviews = conflicts[conflicts > 1]

print("Number of conflicting reviews in the imbalanced dataset:", conflicting_reviews.shape[0])
```

5.3 Handling missing values

Rows with missing or null values, particularly in the review text or rating column, were removed from the remaining data. This step ensured the **imbalanced dataset** was complete and meaningful for analysis.

Code:

```
print(imbalanced_df.isnull().sum())
```

```
imbalanced_df = imbalanced_df.dropna(subset=["Review_text"])
imbalanced_df = imbalanced_df[imbalanced_df["Review_text"].str.strip() != ""]
```

```
print("Shape of the imbalanced dataset after handling missing values:", imbalanced_df.shape)
print("Shape of the imbalanced dataset after handling missing values:", imbalanced_df.shape)
```

5.4 Dropping unnecessary columns

Non-essential columns such as user IDs, product ID, summary, and HelpfulnessNumerator were dropped from the remaining data. These fields did not contribute to the model and could introduce noise or privacy concerns in the imbalanced dataset.

5.5 Lowercasing Text

All review text in the imbalanced dataset was converted to lowercase to maintain uniformity. This helps prevent duplication of tokens, ensuring that words like "Good" and "good" are treated as the same word during analysis.

5.6 Removing URLs

URLs present in the review text were removed using regular expressions.

5.7 Removing emojis and Special characters

Emojis and special symbols may not contribute meaningful context for text analysis (unless specifically required). We remove these characters to focus on the core textual content.

5.8 Removing punctuations

Emojis and special symbols may not contribute meaningful context for text analysis (unless specifically required). We remove these characters to focus on the core textual content.

5.9 Stopwords Removal

Stopwords are commonly used words (like the, is, and, to, in) that usually carry little meaningful information in text analysis. Removing stopwords helps reduce noise and improves the performance of text-based models.

Example:

Before stopword removal:

"This is a very good product and I like it a lot" After

stopword removal:

"This very good product like lot"

Code:

```
import nltk
from nltk.corpus import stopwords

nltk.download("stopwords")
```

```
stop_words = set(stopwords.words("english"))

# Remove stopwords from the imbalanced dataset
imbalanced_df["Review_text"] = imbalanced_df["Review_text"].apply(
    lambda x: " ".join([word for word in x.split() if word.lower() not in stop_words])
)

print("After stopwords removal in the imbalanced dataset:")
print(imbalanced_df["Review_text"].head(10))
```

5.10 Lemmatization

Lemmatization is the process of converting words in the **imbalanced dataset** into their base or dictionary form, known as a lemma. Unlike stemming (which simply chops word endings), lemmatization considers the context and part of speech, producing meaningful root words and improving text consistency for modeling.

Example::

- “running” → “run”
- “better” → “good”
- “cars” → “car”

why lemmatization is better than stemming ?

Meaningful Output:

Stemming just chops off word endings, which may produce non-words.

- “studies” → “studi”
- Lemmatization uses a dictionary to return valid base words.

“studies” → “study”

- Stemming = speed, Lemmatization = correctness.

5.11 Filtering by wordcount

Very short reviews might not contain enough context to be useful, and excessively long reviews could be outliers. We apply filtering to exclude:

- Reviews with fewer than 3 words
- Reviews that exceed 300 words

This ensure that the dataset remains robust and relevant for model training

6. Data visualisation

Box Plot

Box Plot is a visualization that shows the spread and distribution of review lengths across ratings in the dataset. It highlights the median review length, the range of most reviews, and detects outliers such as unusually short or long reviews. This helps in understanding how review size varies with customer ratings.

Histogram

Histogram is a type of data visualization that represents the distribution of a continuous variable by dividing the data into intervals (called bins) and showing the frequency of values falling within each bin as bars. Unlike a bar plot (used for categorical data), a histogram is used to understand the shape, spread, and central tendency of numerical data, such as review lengths or word counts.

1.sample of 1 star rating showing 3

samples for rating 1

1. product arrived labeled jumbo salted peanutsthe peanuts actually small sized unsalted sureerror vendor intended represent product jumbo
2. cats happily eating felidae platinum two years got new bag shape food different tried new foodfirst put bowls bowls sit full kitties touch food ive noticed similar reviews related formula changes past unfortunately need find new food cats eat
3. candy red flavor plan chewy would never buy

2.sample of 2 star rating

1. looking secret ingredient robitussin believe found got addition root beer extract ordered goodmade cherry soda flavor medicinal
2. love eating good watching tv looking movies sweet like transfer zip lock baggie stay fresh taketime eating
3. purchased mango flavor doesnt take like mango hint sweetness unfortunately hint aftertastealmost like licorice ive consuming various sports nutrition products decades im familiar come like taste products ive tried mango flavor one least appealing ive tasted terrible bad enough notice bad taste every sip tak

3.sample of 3 star rating

1. seems little wholesome supermarket brands somewhat mushy doesnt quite much flavor eitherdidnt pass muster kids probably wont buy
2. flavors good however see differce oaker oats brand mushy
3. stuff buy big box stores nothing healthy carbs sugars save money get something least taste

4.sample of 4 star rating

1. confection around centuries light pillowy citrus gelatin nuts case filberts cut tiny squares liberally coated powdered sugar tiny mouthful heaven chewy flavorful highly recommend yummy treat familiar story cs lewis lion witch wardrobe treat seduces edmund selling brother sisters witch
2. got wild hair taffy ordered five pound bag taffy enjoyable many flavors watermelon root beer melon peppermint grape etc complaint bit much redblack licoriceflavored pieces particular favorites kids husband lasted two weeks would recommend brand taffy delightful treat
3. good flavor came securely packed fresh delicious love twizzlers

5.sample of 5 star rating

1. bought several vitality canned dog food products found good quality product looks like stewprocessed meat smells better labrador finicky appreciates product better
2. great taffy great price wide assortment yummy taffy delivery quick taffy lover deal
3. saltwater taffy great flavors soft chewy candy individually wrapped well none candies stucktogether happen expensive version fralingers would highly recommend candy served beachthemed party everyone loved

7. Train-Test-Split

- **Training Set (typically 80%)**: Used to train the machine learning model.
- **Test Set (typically 20%)**: Used to evaluate the model’s performance on unseen data.
- Even with an **imbalanced dataset**, splitting ensures that both sets follow the same **imbalanced class distribution**.

Why stratified split?

- In imbalanced classification problems, some classes (like **1-star or 2-star reviews**) are much smaller than others (like **5-star reviews**).

- If we split randomly **without stratification**, the smaller classes might be missing or underrepresented in the test set.

- **Stratified splitting** makes sure the **same imbalance ratio** is preserved in both training and test sets.

□ This gives a **realistic evaluation**, since the model is tested under the same imbalance conditions as it was trained on.

How it was done?

To prepare the data for model training, the dataset was first shuffled randomly to eliminate any order bias. A **stratified train-test split** was then performed using train_test_split() from sklearn.model_selection with the stratify=y argument to ensure that the **intentionally imbalanced distribution of star ratings** was preserved in both training and testing sets. The dataset was divided into an **80% training set and 20% testing set**. After splitting, all text preprocessing steps—**lowercasing, stopword removal, lemmatization, and cleaning**—were applied **separately** to X_train and X_test to avoid data leakage and ensure model integrity

code:

```
from sklearn.model_selection import train_test_split
from sklearn.feature_extraction.text import TfidfVectorizer

def prepare_train_test(df, text_col="Review_text", target_col="Rating",
                       test_size=0.2, max_features=5000):
    """
    Perform stratified train-test split and TF-IDF vectorization
    while preserving imbalanced class distribution.
```

```
Args:
    df (pd.DataFrame): Input dataframe (can be imbalanced).
    text_col (str): Column with text data.
    target_col (str): Target label column.
    test_size (float): Proportion of test split.
    max_features (int): Number of TF-IDF features.

Returns:
    X_train_vec, X_test_vec, y_train, y_test, vectorizer
"""

# Train-test split (stratified ensures imbalanced proportions are preserved in both sets)
X = df[text_col]
y = df[target_col]
X_train, X_test, y_train, y_test = train_test_split(
    X, y, test_size=test_size, stratify=y, random_state=42
)

# TF-IDF Vectorization
```

```
    vectorizer = TfidfVectorizer(max_features=max_features)
    X_train_vec = vectorizer.fit_transform(X_train)   # fit only on training data
    X_test_vec = vectorizer.transform(X_test)         # transform test data

    return X_train_vec, X_test_vec, y_train, y_test, vectorizer
```

8.Text Vectorization

Machine learning models can't work directly with raw text —they require numerical input. Vectorization is the process of converting text data into numerical features.

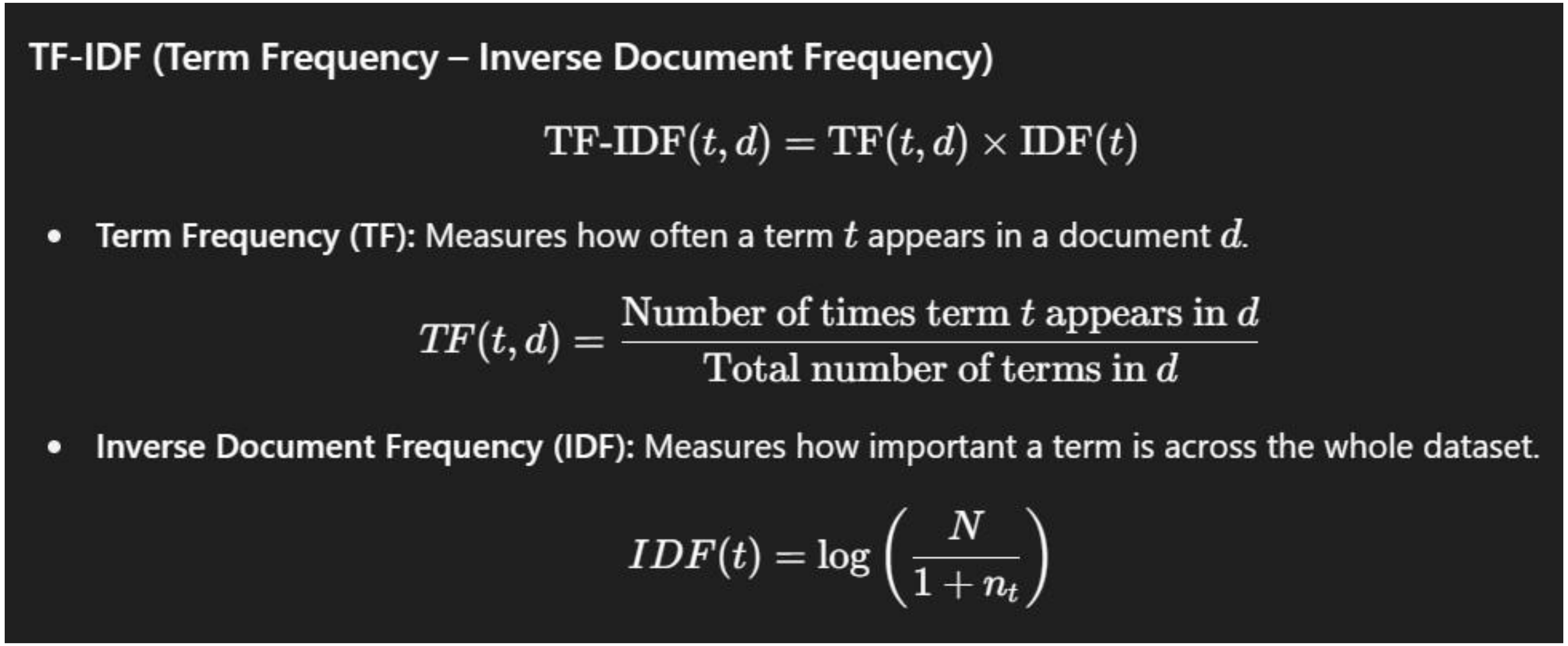
TF-IDF (Term Frequency - Inverse Document Frequency)

TE-IDE is a statistical technique that represents how important a word is to a document relative to the entire corpus.

- TF (Term Frequency): How often a word appears in a document.
- IDF (Inverse Document Frequency): Penalizes common words and highlights rare but important ones.

This approach helps to capture both word relevance and discriminative power, making it better than simple word counts.

FORMULA FOR TF-IDF



TF-IDF (Term Frequency – Inverse Document Frequency)

$$\text{TF-IDF}(t, d) = \text{TF}(t, d) \times \text{IDF}(t)$$

- **Term Frequency (TF):** Measures how often a term t appears in a document d.

$$TF(t, d) = \frac{\text{Number of times term } t \text{ appears in } d}{\text{Total number of terms in } d}$$

- **Inverse Document Frequency (IDF):** Measures how important a term is across the whole dataset.

$$IDF(t) = \log\left(\frac{N}{1 + n_t}\right)$$

code :

```
from sklearn.feature_extraction.text import TfidfVectorizer
from sklearn.model_selection import train_test_split

# Features and target
X = review["Review_text"]   # Preprocessed, cleaned, lemmatized text
y = review["Rating"]        # Target ratings (imbalanced)

# Stratified train-test split (preserves the imbalanced class proportions)
X_train, X_test, y_train, y_test = train_test_split(
    X, y,
    test_size=0.2,
    stratify=y,   # ensures same class proportions in train & test
    random_state=42
)

# TF-IDF Vectorization
tfidf = TfidfVectorizer(
    max_features=5000,   # Top 5000 features
    ngram_range=(1,2),   # Unigrams + bigrams
    stop_words="english" # Remove common stopwords
)

# Fit on training data only to avoid leakage
X_train_tfidf = tfidf.fit_transform(X_train)
X_test_tfidf = tfidf.transform(X_test)

# Show shapes
print("TF-IDF Train shape:", X_train_tfidf.shape)
print("TF-IDF Test shape:", X_test_tfidf.shape)

# Optional: check rating distribution in train and test
print("\nTraining set rating distribution:\n", y_train.value_counts(normalize=True))
print("\nTest set rating distribution:\n", y_test.value_counts(normalize=True))
```