AUTOMATED REVIEW SYSTEM

1. Project Overview

An intelligent system that analyzes customer reviews and predicts corresponding star ratings. It uses natural language processing (NLP) to extract sentiment and key features from textual feedback. The model is trained on labeled review data to learn patterns between language and rating.

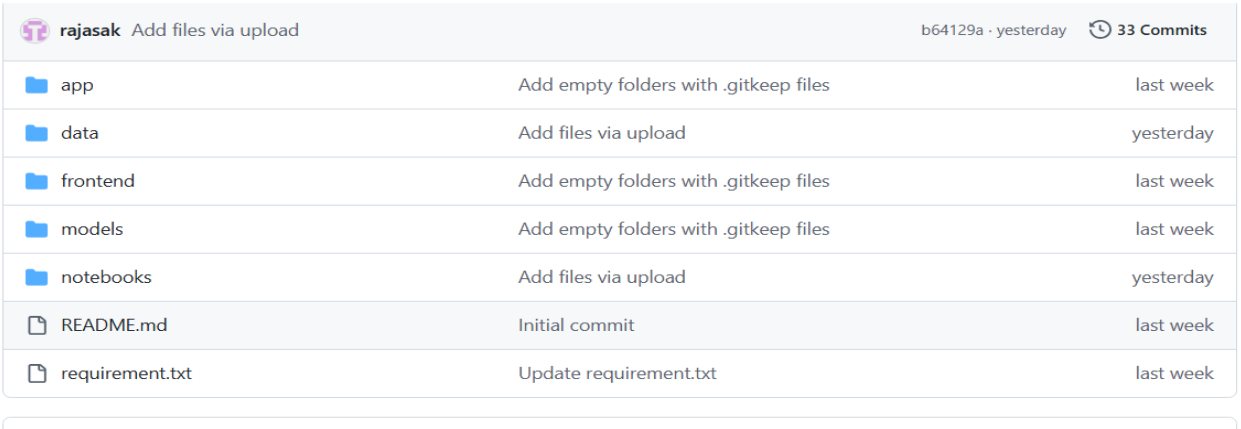
2. Environment Setup

- Installed Python 3.10+ with required libraries: pandas, numpy, matplotlib, seaborn, spacy, scikit-learn, beautifulsoup4, requests, Torch, Transformers
- IDE used: VS Code
- Verified proper functioning of packages for data preprocessing, NLP, and visualization

3. GitHub Project Setup

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

Structure of directory



4. Data Collection

- Two Dataset was collected from Kaggle
- First Dataset collected has 2 lakh rows it was related to Gadgets and cloths
- Second dataset collected has 4 lakh rows it was related to food
- Both the dataset were merged
- link=https://drive.google.com/file/d/11C2vuTiq9czC7uKFdcVhCAbFHqf8OVPt/view?usp=sharing
- Final dataset contains 2 column with Review and Rating
- 1 star=72800, 2 star = 35403, 3 star= 49213, 4 star=89274 , 5 star= 355005

4.1. Balanced dataset

- Link for balanced dataset= https://drive.google.com/file/d/1SH6THfPG-2Rlk7EIIpG8gpQ2qPi3R_d8/view?usp=sharing
- Balanced dataset was created with 23000 rows of each rating

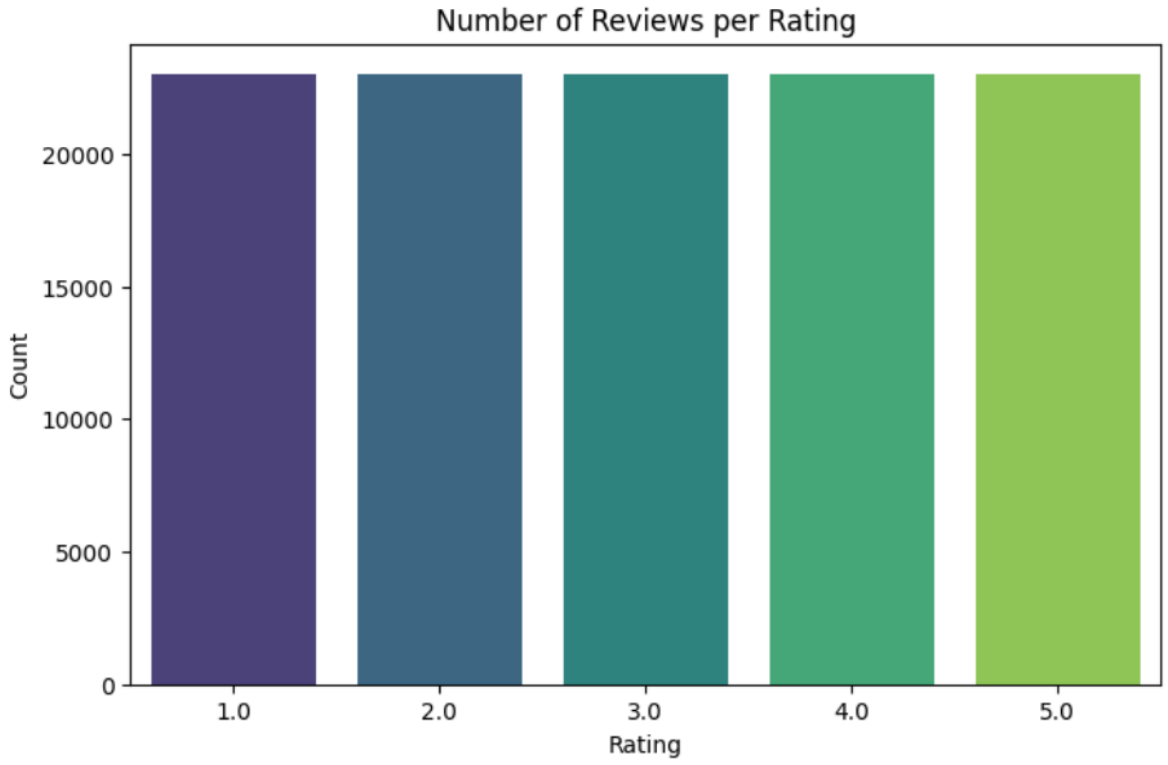


Fig count plot

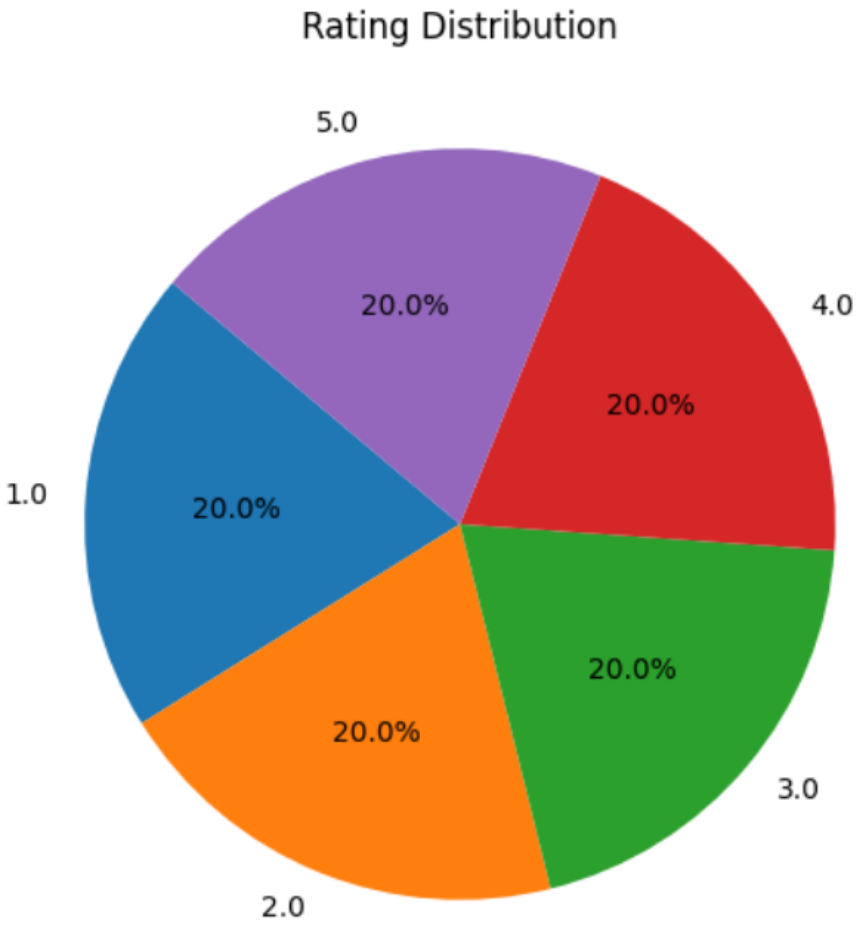


Fig pie chart

5. Data Preprocessing

Effective data preprocessing is essential to improve the performance and accuracy of machine learning models. The following techniques were applied to prepare the raw review dataset for modeling.

5.1 Removing Duplicates

Duplicate rows containing the exact same review and rating were removed to prevent bias and overfitting. This ensured that the dataset only included unique observations.

Code:

```
has_duplicates = df.duplicated().any()
print(has_duplicates)

num_duplicates = df.duplicated().sum()
print(f"Number of duplicate rows: {num_duplicates}")

df.drop_duplicates(inplace=True)
```

5.2 Removing Conflicting Reviews

Some reviews had identical text but different star ratings. These inconsistencies can confuse the model. Such conflicting entries were identified and removed to maintain label clarity.

code:

```
# Filter to only reviews that have more than one unique rating
conflicting_reviews = conflicting_counts[conflicting_counts > 1]
print("Number of conflicting review texts:", conflicting_reviews.shape[0])


conflicting_reviews = df.groupby('Review')['Rating'].nunique()
conflicting_reviews = conflicting_reviews[conflicting_reviews > 1].index
df = df[df['Review'].isin(conflicting_reviews) == False]
```

5.3 Handling Missing Values

Rows with missing or null values—particularly in the review text or rating column—were removed. This step ensured the dataset was complete and meaningful for analysis.

Code:

```
df = df.dropna(subset=['Rating'])
```

5.4 Dropping Unnecessary Columns

Non-essential columns such as review IDs, timestamps, or user identifiers were dropped. These fields did not contribute to the model and could introduce noise or privacy concerns.

5.5 Lowercasing Text

All review text was converted to lowercase to maintain uniformity. This helps prevent duplication of tokens like "Good" and "good" being treated as separate words.

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 Punctuation

Punctuation marks and numbers can disrupt the natural language patterns of the text. By removing them, we simplify the tokenization process and prevent punctuation from being misinterpreted as separate tokens.

Code:

```
#removing punctuations and making lower case
X_train = X_train.str.lower()
X_train = X_train.str.replace(r'\[.*?\]', '', regex=True)
```

```
import re

def clean_text(text):
    text = str(text)
    text = re.sub(r"http\S+|www\S+|https\S+", '', text, flags=re.MULTILINE)
# remove URLs
    text = re.sub(r'<.*?>', '', text)  # remove HTML tags
    text = re.sub(r'[\U00010000-\U0010ffff]', '', text)  # remove emojis
    text = re.sub(r'[^\w\s]', '', text)  # remove punctuation
    text = re.sub(r'[^a-zA-Z0-9\s]', '', text)  # remove special characters
    text = re.sub(r'\s+', ' ', text).strip()  # remove extra whitespace
    return text
```

5.9 Stopwords Removal

Stopwords, such as "the", "is", and "and", are frequently occurring words that might not add significant semantic value. We use libraries like SpaCy to filter these words out, reducing noise and focusing on words that contribute meaning to the reviews, there were total 326 stop words in spacy.

["'d", "'ll", "'m", "'re", "'s", "'ve", 'a', 'about', 'above', 'across', 'after', 'afterwards', '
again', 'against', 'all', 'almost', 'alone', 'along', 'already', 'also', 'although', 'always', 'a
m', 'among', 'amongst', 'amount', 'an', 'and', 'another', 'any', 'anyhow', 'anyone', 'anything',
'anyway', 'anywhere', 'are', 'around', 'as', 'at', 'back', 'be', 'became', 'because', 'become', '
becomes', 'becoming', 'been', 'before', 'beforehand', 'behind', 'being', 'below', 'beside', 'besi
des', 'between', 'beyond', 'both', 'bottom', 'but', 'by', 'ca', 'call', 'can', 'cannot', 'could',
'did', 'do', 'does', 'doing', 'done', 'down', 'due', 'during', 'each', 'eight', 'either', 'eleven
', 'else', 'elsewhere', 'empty', 'enough', 'even', 'ever', 'every', 'everyone', 'everything', 'ev
erywhere', 'except', 'few', 'fifteen', 'fifty', 'first', 'five', 'for', 'former', 'formerly', 'fo
rty', 'four', 'from', 'front', 'full', 'further', 'get', 'give', 'go', 'had', 'has', 'have', 'he'
, 'hence', 'her', 'here', 'hereafter', 'hereby', 'herein', 'hereupon', 'hers', 'herself', 'him',
'himself', 'his', 'how', 'however', 'hundred', 'i', 'if', 'in', 'indeed', 'into', 'is', 'it', 'it
s', 'itself', 'just', 'keep', 'last', 'latter', 'latterly', 'least', 'less', 'made', 'make', 'man
y', 'may', 'me', 'meanwhile', 'might', 'mine', 'more', 'moreover', 'most', 'mostly', 'move', 'muc
h', 'must', 'my', 'myself', "n't", 'name', 'namely', 'neither', 'never', 'nevertheless', 'next',
'nine', 'no', 'nobody', 'none', 'noone', 'nor', 'not', 'nothing', 'now', 'nowhere', 'n‘t', 'n’t',
'of', 'off', 'often', 'on', 'once', 'one', 'only', 'onto', 'or', 'other', 'others', 'otherwise',
'our', 'ours', 'ourselves', 'out', 'over', 'own', 'part', 'per', 'perhaps', 'please', 'put', 'qui
te', 'rather', 're', 'really', 'regarding', 'same', 'say', 'see', 'seem', 'seemed', 'seeming', 's
eems', 'serious', 'several', 'she', 'should', 'show', 'side', 'since', 'six', 'sixty', 'so', 'som
e', 'somehow', 'someone', 'something', 'sometime', 'sometimes', 'somewhere', 'still', 'such', 'ta
ke', 'ten', 'than', 'that', 'the', 'their', 'them', 'themselves', 'then', 'thence', 'there', 'the
reafter', 'thereby', 'therefore', 'therein', 'thereupon', 'these', 'they', 'third', 'this', 'thos
e', 'though', 'three', 'through', 'throughout', 'thru', 'thus', 'to', 'together', 'too', 'top', '
toward', 'towards', 'twelve', 'twenty', 'two', 'under', 'unless', 'until', 'up', 'upon', 'us', 'u
sed', 'using', 'various', 'very', 'via', 'was', 'we', 'well', 'were', 'what', 'whatever', 'when',
'whence', 'whenever', 'where', 'whereafter', 'whereas', 'whereby', 'wherein', 'whereupon', 'where
ver', 'whether', 'which', 'while', 'whither', 'who', 'whoever', 'whole', 'whom', 'whose', 'why',
'will', 'with', 'within', 'without', 'would', 'yet', 'you', 'your', 'yours', 'yourself', 'yoursel
ves', '‘d', '‘ll', '‘m', '‘re', '‘s', '‘ve', '’d', '’ll', '’m', '’re', '’s', '’ve']

Code:

```
#lemmatization and stop word removal
def cleaning(text):
    doc = nlp(text)
    return ' '.join([token.lemma_ for token in doc if not token.is_stop])
```

5.10 Lemmatization

Lemmatization is a text preprocessing technique that reduces words to their base or dictionary form, known as the **lemma**. For example, words like **"running"**, **"ran"**, and **"runs"** are all reduced to the base form **"run"**. Unlike stemming, lemmatization uses linguistic rules and vocabulary, ensuring that the resulting word is meaningful. This helps in grouping similar words and improves model performance by reducing the size of the vocabulary without losing context.

Why lemmatization is better than stemming

Lemmatization is often preferred over stemming because:

1. **Produces Real Words**:

   Lemmatization returns valid dictionary words (e.g., *"running"* → *"run"*), whereas stemming may return incomplete or non-existent words (e.g., *"running"* → *"runn"*).

2. **Context-Aware**:

   Lemmatization considers the context and part of speech (POS) of a word to find its correct root form.
   Stemming blindly trims word endings without understanding grammar.

3. **More Accurate and Clean**:

   Lemmatization provides cleaner and more accurate tokens, which improves model understanding and performance, especially in NLP tasks like sentiment analysis or classification.

5.11 Filtering by Word Count

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 100 words.
  This ensures that the dataset remains robust and relevant for model training.

5.12 Label Encoding for Classification

Since BERT's classification head expects class indices starting from 0, the original star ratings (ranging from 1 to 5) were mapped to class labels 0 to 4.

df['label'] = df['Rating'].astype(int) – 1

6. Data visualization

Box plot

A **box plot** is a visual tool used to display the distribution of numerical data, showing the median, quartiles, and potential outliers. It helps quickly understand how data is spread and identify any extreme values. In this project, box plots were used to compare the word count distribution of reviews across different rating classes.

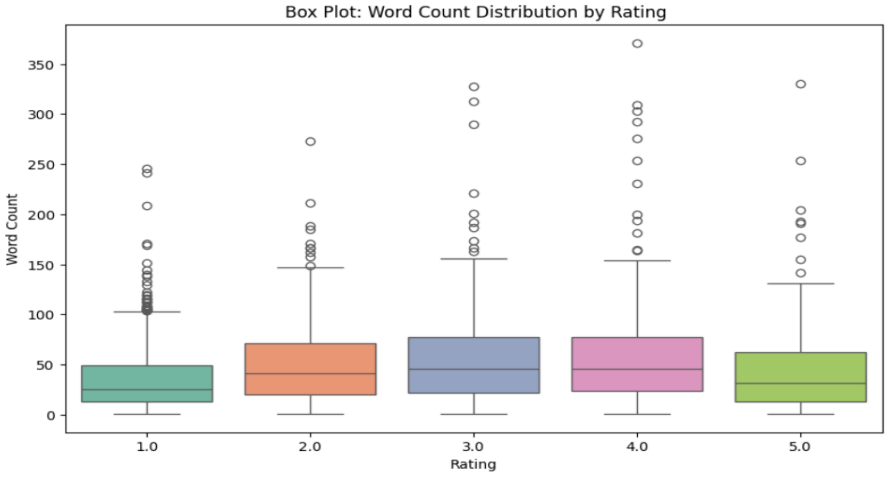


Fig box plot

Histogram

A **histogram** is a graphical representation that shows the distribution of a numeric variable by dividing the data into intervals (bins) and counting how many values fall into each bin. In this project, histograms were used to visualize the **word count distribution** of reviews, helping to identify common review lengths and spot patterns across different rating levels.

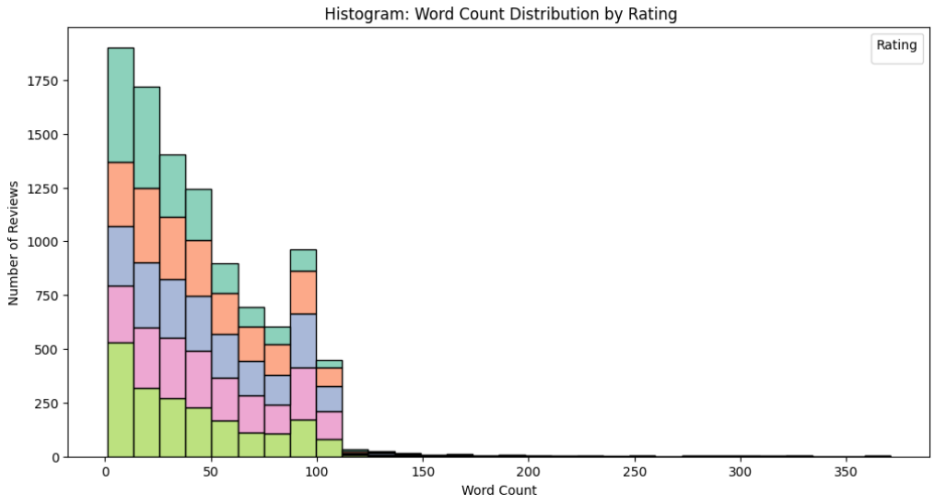


Fig histogram

Samples of 1 star rating:

Showing 5 sample reviews for Rating 1:

1. This shirt didn’t fit correctly so I returned it. I dropped it off at UPS 8/2 and they never refunded me.

2. I really liked this shirt the one time i got to wear it...but when i washed it, according to the directions on the tag, it shrunk! a lot ! the sleeves are now too tight, and it is much shorter. thinking about returning it to the store, but in any case, i cannot wear it agai n.

3. I have the purple jacket is short on sleeves and pants were short to very disappointed I have the black,red and grey and they fitt ed perfectly I don’t understand why this purple suit was made like this and they are all the same size smh

4. Oh I am so, so, sad. I thought I had found the perfect jeans. I bought a pair about a year ago and loved them. So, I ordered thes e. Imagine my surprise when I realized there were no front pockets. I mean. Really? I do not want to carry a purse or wear more l ayers of clothes. I want to feel skinny in a pair of jeans, and have pockets. Disappointing.

5. It was too big for my daughter, I returned it from UPS and so far I haven't received the credit to get another one.

Samples of 2 star rating

Showing 5 sample reviews for Rating 2:

1. 👎

2. Material to heavy for summer.

3. Based on the other reviews, i sized down from my usual 6p to a 2p, but this dress was still ridiculously huge and extremely unf lattering. i could tell the minute i took it out of the package it wouldn't work. i can't imagine this would flatter very many people. the front photo of the model is incredibly deceptive. very disappointed--this will be going back for sure.

4. Advertised as loose fit, but definitely snug and way too short.

5. Not too fond of the material and the way it looks like a rain coat

Samples of 3 star rating

Showing 5 sample reviews for Rating 3:

1. Pants were fine but pockets ripped immediately. Only buy if you know how to sew.

2. I love the fabric however the overall fit did not work for me.
i think the arms are much smaller than the overall shirt.

3. The look and feel of the swim trunks are great but the quality should be higher for the price. After one wash and wear the waist band stitching started to come loose. I would expect some wear and tear after several uses but not after one.

4. Did not like fabric, does not drape well.

5. The wrong color was sent to me. I kept them anyways, but I’m not crazy about the fit of these. The tag on the outside waistban d somehow digs up into my skin when i sit, making it mildly uncomfortable. They are a nice Jean quality though.

Samples of 4 star rating

Showing 5 sample reviews for Rating 4:

1. The fabric is nice and the color is a rich jewel-tone. i have a couple of very similar shirts from a similar store that are several y ears old. those fit a bit more loss sly around the stomach (not baggy, just body-skimming) which made them more flattering for m ore body types. this shirt works if you have a little padding because of the gathered folds, but it probably wouldn't be great for so meone carrying a lot of extra weight around their middle. the knot also has a tendency to twist exposing t

2. Style is perfect, year around wear.

3. Bought these in 28 had to return for a 27p . love them!! i order the 2 other colors

4. I really love the look of this sweater and it seems to be of great quality. i will say the fit is a bit odd. the sweater is on the short side but is very roomy through the neck and shoulders. i ordered a small (5'6"; 120lbs) and would change for an xs but i'm afraid i t would be cropped. i'm keeping it but wish it had a more uniform fit.
really beautify workmanship though.

5. These jeans for great and were flattering. Perfect length for me which is always a problem I have with high waisted pants. The y were long enough but didn’t drag under foot. I love the double buttons!! Good quality jeans all around… good purchase!!

Samples of 5 star rating

Showing 5 sample reviews for Rating 5:

1. Very comfortable and fits well.

2. This top is really pretty and nice quality. runs big - i went down a size, and its perfect. coloring is more subtle in person than in the photo.

3. Happy with fit and quality

4. As a full time photographer, I am always looking for breathable, cute and professional shirts to wear to sessions and weddings. I love this shirt, and it’s honestly perfect for every occasion. Time to go buy it in every color lol

5. I love how versatile this dress is! Listen to the reviews as if you do have a little bit of a belly or pooch, def size up. I’m normall y a 4, 5’9 and weight 150 pounds. I ordered the 8-10 and I’m so glad I did. Fits very well- may have to wear spanx only bc I do n ot have a flat stomach. If you do, order your normal size. Fits very well in the chest and the rest of my body.

7. Train-Test Split

Train-Test Split is a technique to divide the dataset into two separate sets:

- **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.

This separation ensures that the model generalizes well and is not just memorizing the training data.

Why Stratified Split?

In classification problems like review rating prediction, stratified splitting is important to maintain class balance (equal distribution of ratings) in both training and testing sets.

Without stratification, some rating classes (like 1-star or 5-star) may be underrepresented in the test set, leading to biased evaluation.

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 all star ratings were **proportionally represented** in both training and testing sets. The dataset was split using an **80% training and 20% testing ratio**. After splitting, all **text preprocessing steps**—including lowercasing, lemmatization, stopword removal, and cleaning—were applied **separately** to `X_train` and `X_test` to **prevent data leakage** and maintain model integrity.

Code:

```
# Shuffle the balanced DataFrame
df = df.sample(frac=1, random_state=42).reset_index(drop=True)


from sklearn.model_selection import train_test_split


x=df['Review']
y=df['Rating']


X_train, X_test, y_train, y_test = train_test_split(
    x, y, test_size=0.2, random_state=42, stratify=y
)
```

8. Conversion to Hugging Face Datasets

The train_df and test_df were converted to datasets.Dataset objects from Hugging Face to support seamless integration with tokenization and training workflows:

Code:

from datasets import Dataset

train_dataset = Dataset.from_pandas(train_df)

test_dataset = Dataset.from_pandas(test_df)

9. Tokenization for BERT

Used the BERT tokenizer from Hugging Face's Transformers library (bert-base-uncased):

Tokenization included:

- Padding to a fixed length (64 tokens)
- Truncating long sequences

Code:

```
from transformers import AutoTokenizer

model_name = "bert-base-uncased"

tokenizer = AutoTokenizer.from_pretrained(model_name)


def tokenize(example):

    return tokenizer(example["text"], truncation=True, padding="max_length", max_length=64)


train_dataset = train_dataset.map(tokenize, batched=True)

test_dataset = test_dataset.map(tokenize, batched=True)
```

11. Formatting for PyTorch

The tokenized datasets were formatted for PyTorch-based training

Code:

```
train_dataset.set_format(type="torch", columns=["input_ids", "attention_mask", "label"])

test_dataset.set_format(type="torch", columns=["input_ids", "attention_mask", "label"])
```

12. Training the model

Algorithm: Bert

Link= https://github.com/rajasak/automated-review-rating-system/blob/main/notebooks/deep%20learning/bert.pdf