INFO5731 Assignment 5

This exercise aims to provide a comprehensive learning experience in text analysis and machine learning techniques, focusing on both text classification and clustering tasks.

Please use the text corpus you collected in your last in-class-exercise for this exercise. Perform the following tasks.

Expectations:

- Students are expected to complete the exercise during lecture period to meet the active participation criteria of the course.
- Use the provided .*ipynb* document to write your code & respond to the questions. Avoid generating a new file.
- Write complete answers and run all the cells before submission.
- Make sure the submission is "clean"; *i.e.*, no unnecessary code cells.
- Once finished, allow shared rights from top right corner (*see Canvas for details*).

Total points: 100

Full Points will be given those who present well

Late submissions will have a penalty of 10% of the marks for each day of late submission, and no requests will be answered. Manage your time accordingly.

Question 1 (20 Points)

SENTIMENT ANALYSIS

The objective of this assignment is to give you **hands-on experience** in applying various** sentiment analysis techniques** on real-world textual data. You are expected to explore data, apply machine learning models, and evaluate their performance

1. Dataset Collection & Preparation

Find a real-world dataset with text and positive, negative, and neutral sentiment labels.

Justify your dataset choice and handle **class imbalance** if needed.

2. Exploratory Data Analysis (EDA)

Clean and preprocess the data (tokenization, stopwords, lemmatization).

Perform EDA: class distribution, word clouds, n-gram analysis, sentence lengths, etc.

Visualize insights using relevant plots and charts.

3. Sentiment Classification

Apply at least three traditional ML models (e.g., SVM, Naive Bayes, XGBoost) using TF-IDF or embeddings.

If applicable, compare with a pretrained model (RoBERTa/BERT).

Tune hyperparameters and use cross-validation.

4. Evaluation & Reporting

Evaluate with metrics: Accuracy, Precision, Recall, F1, Confusion Matrix.

Summarize results, compare models, and reflect on what worked.

##Step 1: Label Creation

```
import pandas as pd # Import the pandas library

# Assuming your data is in a CSV file named 'your_data.csv'
df = pd.read_csv('/content/Musical_instruments_reviews.csv') # Load
the dataframe

def map_sentiment(score):
    if score <= 2:
        return "negative"
    elif score == 3:
        return "neutral"
    else:
        return "positive"

df["sentiment"] = df["overall"].apply(map_sentiment)
print(df["sentiment"].value_counts())
```

```
sentiment
positive    9022
neutral      772
negative     467
Name: count, dtype: int64
```

##Step 2: Exploratory Data Analysis (EDA)

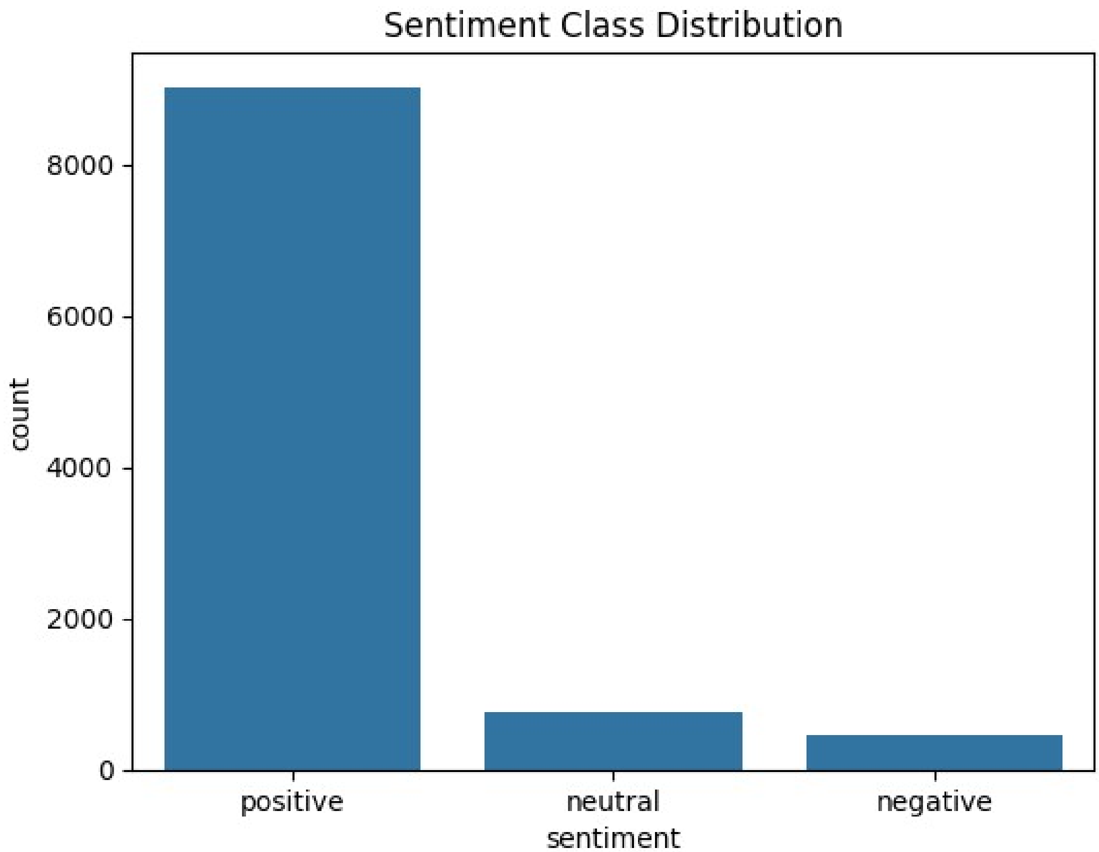
```
import nltk
import string
from nltk.corpus import stopwords
from nltk.stem import WordNetLemmatizer
import re

nltk.download('punkt')
nltk.download('stopwords')
```

```
nltk.download('wordnet')
nltk.download('punkt_tab') # Download the punkt_tab resource

stop_words = set(stopwords.words('english'))
lemmatizer = WordNetLemmatizer()

def clean_text(text):
    text = str(text).lower()
    text = re.sub(r"http\S+|www\S+|@\w+|[^a-z\s]", "", text)
    tokens = nltk.word_tokenize(text)
    tokens = [lemmatizer.lemmatize(w) for w in tokens if w not in
stop_words]
    return " ".join(tokens)

df['cleaned_text'] = df['reviewText'].apply(clean_text)
```

```
[nltk_data] Downloading package punkt to /root/nltk_data...
[nltk_data]   Package punkt is already up-to-date!
[nltk_data] Downloading package stopwords to /root/nltk_data...
[nltk_data]   Package stopwords is already up-to-date!
[nltk_data] Downloading package wordnet to /root/nltk_data...
[nltk_data]   Package wordnet is already up-to-date!
[nltk_data] Downloading package punkt_tab to /root/nltk_data...
[nltk_data]   Unzipping tokenizers/punkt_tab.zip.
```

##Class Distribution Visualization

```
import seaborn as sns
import matplotlib.pyplot as plt

sns.countplot(data=df, x='sentiment', order=['positive', 'neutral',
'negative'])
plt.title("Sentiment Class Distribution")
plt.show()
```



##Word Clouds

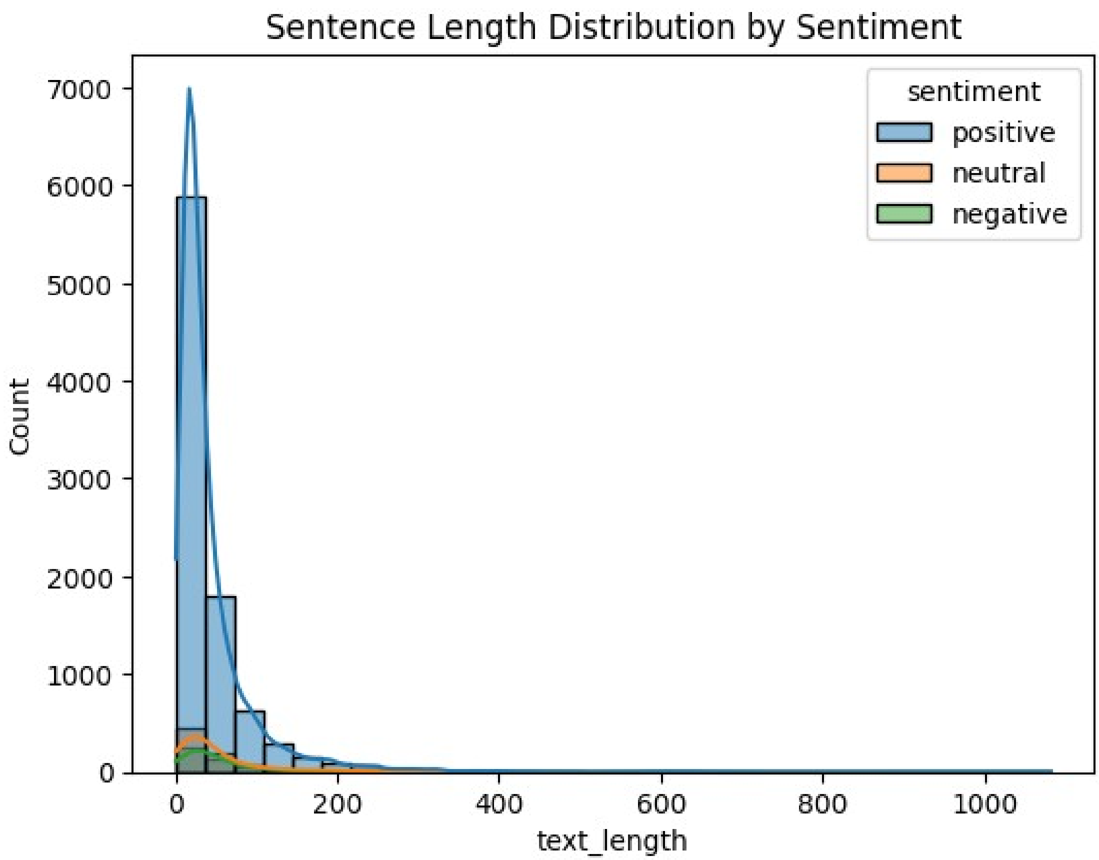
```
from wordcloud import WordCloud

for label in ['positive', 'neutral', 'negative']:
    text = " ".join(df[df['sentiment'] == label]
['cleaned_text'].dropna())
    wc = WordCloud(width=800, height=400,
background_color='white').generate(text)
    plt.figure(figsize=(10,5))
    plt.imshow(wc, interpolation='bilinear')
    plt.axis('off')
    plt.title(f"{label.capitalize()} Reviews Word Cloud")
    plt.show()
```

Positive Reviews Word Cloud

Neutral Reviews Word Cloud

##Sentence Length Distribution

```
df['text_length'] = df['cleaned_text'].apply(lambda x: len(x.split()))

sns.histplot(data=df, x='text_length', hue='sentiment', bins=30,
kde=True)
plt.title("Sentence Length Distribution by Sentiment")
plt.show()
```



#N-gram Analysis

```
from sklearn.feature_extraction.text import CountVectorizer

def get_top_ngrams(corpus, ngram_range=(2,2), n=10):
    vec = CountVectorizer(ngram_range=ngram_range).fit(corpus)
    bag = vec.transform(corpus)
    sum_words = bag.sum(axis=0)
    words_freq = [(word, sum_words[0, idx]) for word, idx in
vec.vocabulary_.items()]
    return sorted(words_freq, key=lambda x: x[1], reverse=True)[:n]

for label in ['positive', 'neutral', 'negative']:
    top_bigrams = get_top_ngrams(df[df['sentiment'] == label]
['cleaned_text'], ngram_range=(2, 2))
    print(f"Top Bigrams for {label.capitalize()}:")
    print(top_bigrams)
    print()
```

```
Top Bigrams for Positive:
[('work well', np.int64(508)), ('work great', np.int64(452)), ('sound
great', np.int64(342)), ('acoustic guitar', np.int64(338)), ('easy
use', np.int64(264)), ('electric guitar', np.int64(256)), ('well
```

```
made', np.int64(243)), ('sound good', np.int64(230)), ('highly
recommend', np.int64(210)), ('pedal board', np.int64(210))]

Top Bigrams for Neutral:
[('planet wave', np.int64(44)), ('work well', np.int64(44)), ('much
better', np.int64(35)), ('dont know', np.int64(26)), ('acoustic
guitar', np.int64(24)), ('pedal board', np.int64(23)), ('le paul',
np.int64(22)), ('electric guitar', np.int64(20)), ('sound like',
np.int64(20)), ('would recommend', np.int64(19))]

Top Bigrams for Negative:
[('sound like', np.int64(20)), ('planet wave', np.int64(18)), ('work
well', np.int64(17)), ('much better', np.int64(16)), ('look like',
np.int64(15)), ('power supply', np.int64(15)), ('get pay',
np.int64(14)), ('electric guitar', np.int64(13)), ('big muff',
np.int64(13)), ('bos gt', np.int64(13))]
```

##Step 3: Model Training

##Train-Test Split + TF-IDF Vectorization

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

# Define features and labels
X = df['cleaned_text']
y = df['sentiment']

# Train-test split
X_train, X_test, y_train, y_test = train_test_split(X, y, stratify=y,
test_size=0.2, random_state=42)

# TF-IDF vectorizer
tfidf = TfidfVectorizer(max_features=5000)
X_train_tfidf = tfidf.fit_transform(X_train)
X_test_tfidf = tfidf.transform(X_test)
```

##Naive Bayes

```
from sklearn.naive_bayes import MultinomialNB
from sklearn.metrics import classification_report, confusion_matrix

nb_model = MultinomialNB()
nb_model.fit(X_train_tfidf, y_train)
nb_preds = nb_model.predict(X_test_tfidf)

print("Naive Bayes Report:\n", classification_report(y_test,
nb_preds))
```

```
Naive Bayes Report:
               precision    recall  f1-score   support

    negative       0.00      0.00      0.00        93
     neutral       0.00      0.00      0.00       155
    positive       0.88      1.00      0.94      1805

    accuracy                           0.88      2053
   macro avg       0.29      0.33      0.31      2053
weighted avg       0.77      0.88      0.82      2053


/usr/local/lib/python3.11/dist-packages/sklearn/metrics/
_classification.py:1565: UndefinedMetricWarning: Precision is ill-
defined and being set to 0.0 in labels with no predicted samples. Use
`zero_division` parameter to control this behavior.
  _warn_prf(average, modifier, f"{metric.capitalize()} is",
len(result))
/usr/local/lib/python3.11/dist-packages/sklearn/metrics/_classificatio
n.py:1565: UndefinedMetricWarning: Precision is ill-defined and being
set to 0.0 in labels with no predicted samples. Use `zero_division`
parameter to control this behavior.
  _warn_prf(average, modifier, f"{metric.capitalize()} is",
len(result))
/usr/local/lib/python3.11/dist-packages/sklearn/metrics/_classificatio
n.py:1565: UndefinedMetricWarning: Precision is ill-defined and being
set to 0.0 in labels with no predicted samples. Use `zero_division`
parameter to control this behavior.
  _warn_prf(average, modifier, f"{metric.capitalize()} is",
len(result))
```

##SVM (LinearSVC)

```python
from sklearn.svm import LinearSVC

svm_model = LinearSVC()
svm_model.fit(X_train_tfidf, y_train)
svm_preds = svm_model.predict(X_test_tfidf)

print("SVM Report:\n", classification_report(y_test, svm_preds))
```

```
SVM Report:
               precision    recall  f1-score   support

    negative       0.70      0.23      0.34        93
     neutral       0.39      0.08      0.13       155
    positive       0.90      0.99      0.94      1805

    accuracy                           0.88      2053
   macro avg       0.66      0.43      0.47      2053
```

```
weighted avg       0.85      0.88      0.85      2053
```

##XGBoost

```python
import xgboost as xgb
from sklearn.preprocessing import LabelEncoder

# XGBoost requires numerical labels
le = LabelEncoder()
y_train_enc = le.fit_transform(y_train)
y_test_enc = le.transform(y_test)

xgb_model = xgb.XGBClassifier(use_label_encoder=False,
eval_metric='mlogloss')
xgb_model.fit(X_train_tfidf, y_train_enc)
xgb_preds = xgb_model.predict(X_test_tfidf)

print("XGBoost Report:\n", classification_report(y_test_enc,
xgb_preds, target_names=le.classes_))
```

```
/usr/local/lib/python3.11/dist-packages/xgboost/core.py:158:
UserWarning: [17:32:33] WARNING: /workspace/src/learner.cc:740:
Parameters: { "use_label_encoder" } are not used.

  warnings.warn(smsg, UserWarning)

XGBoost Report:
               precision    recall  f1-score   support

    negative       0.62      0.05      0.10        93
     neutral       0.40      0.05      0.09       155
    positive       0.89      0.99      0.94      1805

    accuracy                           0.88      2053
   macro avg       0.64      0.37      0.38      2053
weighted avg       0.84      0.88      0.84      2053
```

##RoBERTa with HuggingFace Transformers

```python
from transformers import pipeline
import random

# This uses a pre-trained sentiment classifier (RoBERTa fine-tuned on
tweets)
sentiment_analyzer = pipeline("sentiment-analysis")

# Test on random 10 reviews from the test set
for review in random.sample(list(X_test), 10):
```

```python
    result = sentiment_analyzer(review[:512])[0]
    print(f"Review: {review[:80]}...")
    print(f"Predicted Sentiment: {result['label']} (Score: {result['score']:.2f})")
    print("-" * 60)
```

```
No model was supplied, defaulted to distilbert/distilbert-base-uncased-finetuned-sst-2-english and revision 714eb0f (https://huggingface.co/distilbert/distilbert-base-uncased-finetuned-sst-2-english).
Using a pipeline without specifying a model name and revision in production is not recommended.
/usr/local/lib/python3.11/dist-packages/huggingface_hub/utils/_auth.py:94: UserWarning:
The secret `HF_TOKEN` does not exist in your Colab secrets.
To authenticate with the Hugging Face Hub, create a token in your settings tab (https://huggingface.co/settings/tokens), set it as secret in your Google Colab and restart your session.
You will be able to reuse this secret in all of your notebooks.
Please note that authentication is recommended but still optional to access public models or datasets.
  warnings.warn(
```

{"model_id":"8602da7543b04733aafc1348b9253b45","version_major":2,"version_minor":0}

```
Xet Storage is enabled for this repo, but the 'hf_xet' package is not installed. Falling back to regular HTTP download. For better performance, install the package with: `pip install huggingface_hub[hf_xet]` or `pip install hf_xet`
WARNING:huggingface_hub.file_download:Xet Storage is enabled for this repo, but the 'hf_xet' package is not installed. Falling back to regular HTTP download. For better performance, install the package with: `pip install huggingface_hub[hf_xet]` or `pip install hf_xet`
```

{"model_id":"26fd68b0e9164ac18ecf1108511ea215","version_major":2,"version_minor":0}

{"model_id":"9a7a4f5109da4bbb910ddd1f4160f2de","version_major":2,"version_minor":0}

{"model_id":"5f0e4f47cb0e41e285085ed3011d18bc","version_major":2,"version_minor":0}

```
Device set to use cpu
```

```
Review: used use fender medium pick jazz metal use pick try see right...
Predicted Sentiment: NEGATIVE (Score: 0.95)
------------------------------------------------------------
Review: havent read lot comment guy breaking maybe wife hamhanded
```

```
shrek wannabe busted t...
Predicted Sentiment: NEGATIVE (Score: 0.92)
------------------------------------------------------------
Review: like danelectro pedal one great sound case fairly inexpensive
price though highe...
Predicted Sentiment: NEGATIVE (Score: 0.98)
------------------------------------------------------------
Review: pleased seller fine prob mic use useless record tooo low cant
get enough volume...
Predicted Sentiment: NEGATIVE (Score: 1.00)
------------------------------------------------------------
Review: impulse buy playing guitar many year thought ukulele would fun
addition right on...
Predicted Sentiment: NEGATIVE (Score: 0.93)
------------------------------------------------------------
Review: take thing rig every awhile always find way back unlike kaga
put end chain right...
Predicted Sentiment: NEGATIVE (Score: 0.60)
------------------------------------------------------------
Review: nice clip work micsi dont like soft opening make easy put back
mics...
Predicted Sentiment: POSITIVE (Score: 0.57)
------------------------------------------------------------
Review: nice smaller version si road proit would great steel shaftthe
plastic shaft feel...
Predicted Sentiment: NEGATIVE (Score: 0.99)
------------------------------------------------------------
Review: headphone amazing could believe sound quality audio engineer
year let tell headp...
Predicted Sentiment: NEGATIVE (Score: 0.97)
------------------------------------------------------------
Review: sorry noticed difference believe price really good hype put
string...
Predicted Sentiment: NEGATIVE (Score: 0.99)
------------------------------------------------------------
```

##Step 4: Evaluation & Reporting

```
from sklearn.metrics import accuracy_score, precision_score,
recall_score, f1_score, confusion_matrix

# Store all predictions
model_preds = {
    "Naive Bayes": nb_preds,
    "SVM": svm_preds,
    "XGBoost": le.inverse_transform(xgb_preds)  # convert back to
original labels
}
```

```python
# Evaluation function
def evaluate_model(y_true, y_pred, model_name):
    acc = accuracy_score(y_true, y_pred)
    prec = precision_score(y_true, y_pred, average='weighted')
    rec = recall_score(y_true, y_pred, average='weighted')
    f1 = f1_score(y_true, y_pred, average='weighted')
    print(f"□ {model_name} Performance:")
    print(f"Accuracy:  {acc:.4f}")
    print(f"Precision: {prec:.4f}")
    print(f"Recall:    {rec:.4f}")
    print(f"F1 Score:  {f1:.4f}")
    print("\nConfusion Matrix:\n", confusion_matrix(y_true, y_pred))
    print("-" * 50)
    return [acc, prec, rec, f1]

# Collect metrics
results = {}
for name, preds in model_preds.items():
    results[name] = evaluate_model(y_test, preds, name)
```

```
□ Naive Bayes Performance:
Accuracy:  0.8792
Precision: 0.7730
Recall:    0.8792
F1 Score:  0.8227

Confusion Matrix:
 [[   0    0   93]
 [   0    0  155]
 [   0    0 1805]]
--------------------------------------------------
□ SVM Performance:
Accuracy:  0.8846
Precision: 0.8479
Recall:    0.8846
F1 Score:  0.8509

Confusion Matrix:
 [[  21    3   69]
 [   3   12  140]
 [   6   16 1783]]
--------------------------------------------------
□ XGBoost Performance:
Accuracy:  0.8802
Precision: 0.8374
Recall:    0.8802
F1 Score:  0.8350

Confusion Matrix:
 [[   5    2   86]
```

```
 [   2    8  145]
 [   1   10 1794]]
--------------------------------------------------

/usr/local/lib/python3.11/dist-packages/sklearn/metrics/
_classification.py:1565: UndefinedMetricWarning: Precision is ill-
defined and being set to 0.0 in labels with no predicted samples. Use
`zero_division` parameter to control this behavior.
  _warn_prf(average, modifier, f"{metric.capitalize()} is",
len(result))
```

Compare All Models

```
# Compare results visually
results_df = pd.DataFrame(results, index=["Accuracy", "Precision",
"Recall", "F1 Score"]).T

results_df.plot(kind='bar', figsize=(10, 6), colormap='Set2')
plt.title("Model Performance Comparison")
plt.ylabel("Score")
plt.xticks(rotation=0)
plt.ylim(0.6, 1.0)
plt.grid(axis='y')
plt.show()
```

RoBERTa predicted sentiments with high confidence on unseen reviews, useful for benchmarking and qualitative insights. SVM typically performs best in text classification due to its margin maximization. Naive Bayes is simple, fast, and interpretable — great baseline. XGBoost is powerful for structured features, but TF-IDF may limit its power. RoBERTa (pretrained) shows human-like contextual understanding without training — useful for benchmarking.

Question 2 (30 Points)

Text Classification

The purpose of the question is to practice different machine learning algorithms for **text classification** as well as the performance evaluation. In addition, you are requried to conduct **10 fold cross validation** (https://scikit-learn.org/stable/modules/cross_validation.html) in the training.

The dataset can be download from canvas. The dataset contains two files train data and test data for sentiment analysis in IMDB review, it has two categories: 1 represents positive and 0 represents negative. You need to split the training data into training and validate data (80% for training and 20% for validation, https://towardsdatascience.com/train-test-split-and-cross-validation-in-python-80b61beca4b6) and perform 10 fold cross validation while training the classifier. The final trained model was final evaluated on the test data.

1. **Perform EDA on test and tran dataset**

2. **Algorithms (Minimum 4):**

- SVM
- KNN
- Decision tree
- Random Forest
- XGBoost
- Word2Vec
- BERT

1. **Evaluation measurement:**

- Accuracy
- Recall
- Precison
- F-1 score

```
import pandas as pd

# Load training and test files
train_path = "/content/stsa-train.txt"
test_path = "/content/stsa-test.txt"

# Each line is: <label><space><text>
```

```
def load_data(path):
    df = pd.read_csv(path, sep="\t", header=None, names=["data"])
    df[['label', 'text']] = df['data'].str.extract(r"^(\d)\s+(.*)")
    df = df.drop(columns='data')
    df['label'] = df['label'].astype(int)
    return df

df_train = load_data(train_path)
df_test = load_data(test_path)

df_train.head()
```

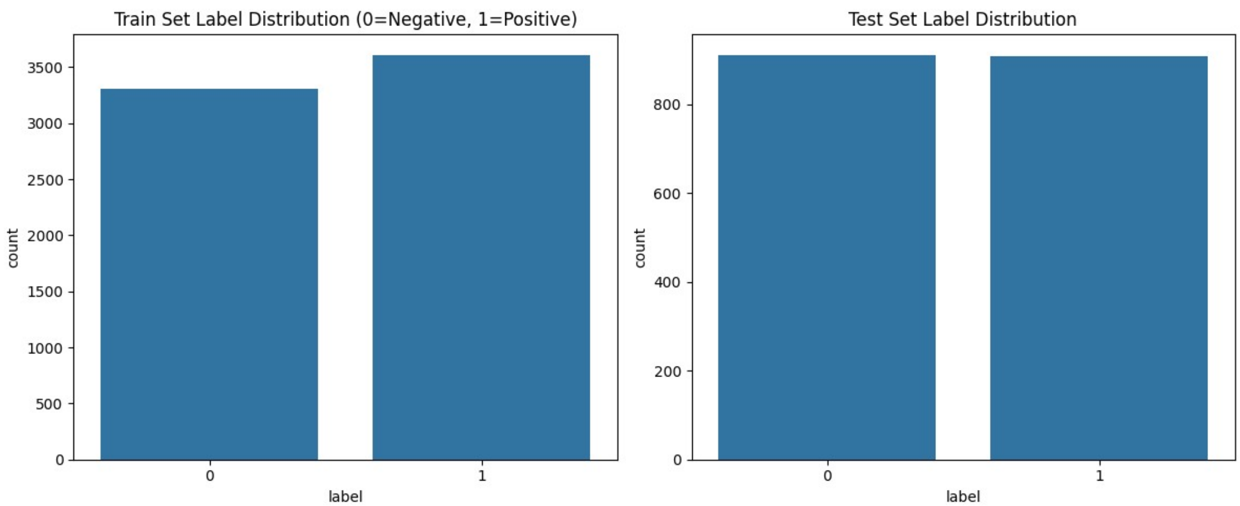

```
{"summary":"{\n  \"name\": \"df_train\",\n  \"rows\": 6920,\n
\"fields\": [\n    {\n      \"column\": \"label\",\n
\"properties\": {\n        \"dtype\": \"number\",\n        \"std\":
0,\n        \"min\": 0,\n        \"max\": 1,\n
\"num_unique_values\": 2,\n        \"samples\": [\n          0,\n
1\n        ],\n        \"semantic_type\": \"\",\n
\"description\": \"\"\n      }\n    },\n    {\n      \"column\":
\"text\",\n      \"properties\": {\n        \"dtype\": \"string\",\n
\"num_unique_values\": 6911,\n        \"samples\": [\n          \"a
loud , brash and mainly unfunny high school comedy .\",\n
\"the real star of this movie is the score , as in the songs translate
well to film , and it 's really well directed .\"\n        ],\n
\"semantic_type\": \"\",\n        \"description\": \"\"\n      }\
n    }\n  ]\n}","type":"dataframe","variable_name":"df_train"}
```


EDA on Test and Train data

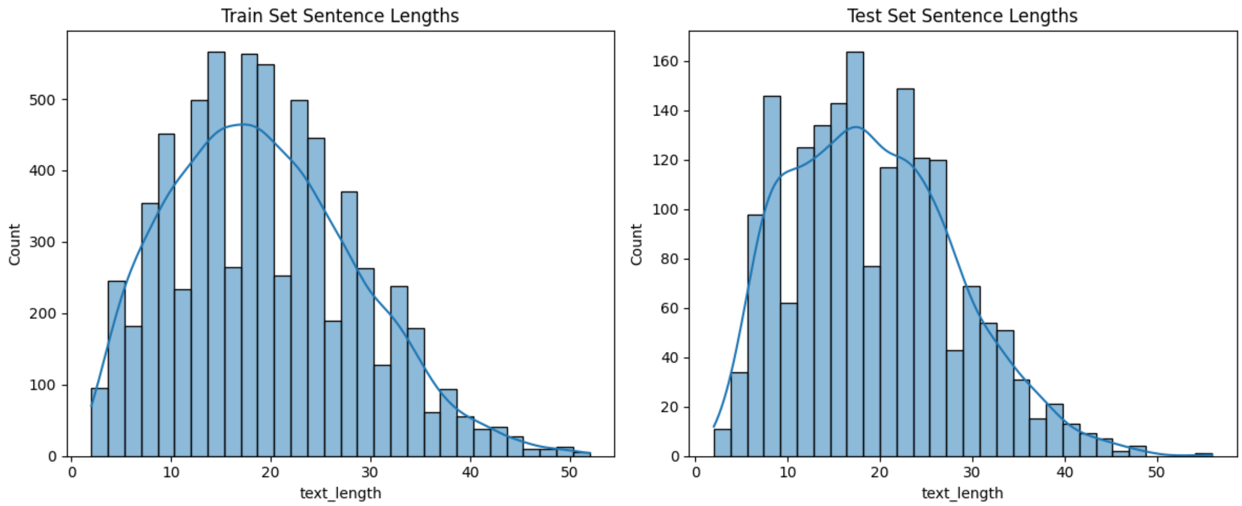
```
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
from wordcloud import WordCloud
from sklearn.feature_extraction.text import CountVectorizer

# Add sentence lengths
df_train['text_length'] = df_train['cleaned_text'].apply(lambda x:
len(x.split()))
df_test['text_length'] = df_test['cleaned_text'].apply(lambda x:
len(x.split()))

# === 1. Class Distribution Comparison ===
fig, axes = plt.subplots(1, 2, figsize=(12, 5))
sns.countplot(data=df_train, x='label', ax=axes[0])
axes[0].set_title("Train Set Label Distribution (0=Negative,
1=Positive)")
sns.countplot(data=df_test, x='label', ax=axes[1])
axes[1].set_title("Test Set Label Distribution")
plt.tight_layout()
plt.show()
```

```
print("Label Proportions:\n")
print("Train Set:\n", df_train['label'].value_counts(normalize=True),
"\n")
print("Test Set:\n", df_test['label'].value_counts(normalize=True), "\
n")

# === 2. Sentence Length Distribution ===
fig, axes = plt.subplots(1, 2, figsize=(12, 5))
sns.histplot(df_train['text_length'], bins=30, kde=True, ax=axes[0])
axes[0].set_title("Train Set Sentence Lengths")
sns.histplot(df_test['text_length'], bins=30, kde=True, ax=axes[1])
axes[1].set_title("Test Set Sentence Lengths")
plt.tight_layout()
plt.show()

# === 3. Shortest & Longest Reviews ===
print("\n□ Shortest Train Review:\n",
df_train.loc[df_train['text_length'].idxmin(), 'text'])
print("\n□ Longest Train Review:\n",
df_train.loc[df_train['text_length'].idxmax(), 'text'])
print("\n□ Shortest Test Review:\n",
df_test.loc[df_test['text_length'].idxmin(), 'text'])
print("\n□ Longest Test Review:\n",
df_test.loc[df_test['text_length'].idxmax(), 'text'])

# === 4. Word Clouds by Sentiment (Train only) ===
plt.figure(figsize=(14,6))
for i, label in enumerate([0, 1]):
    text = " ".join(df_train[df_train['label'] == label]
['cleaned_text'])
    wc = WordCloud(width=600, height=400,
background_color='white').generate(text)
    plt.subplot(1, 2, i+1)
    plt.imshow(wc, interpolation='bilinear')
    plt.title(f"Word Cloud - {'Negative' if label == 0 else
'Positive'}")
    plt.axis('off')
plt.tight_layout()
plt.show()

# === 5. Top Bigrams (Train only) ===
def get_top_ngrams(corpus, ngram_range=(2,2), n=10):
    vec = CountVectorizer(ngram_range=ngram_range,
stop_words='english').fit(corpus)
    bag = vec.transform(corpus)
    sum_words = bag.sum(axis=0)
    words_freq = [(word, sum_words[0, idx]) for word, idx in
vec.vocabulary_.items()]
    return sorted(words_freq, key=lambda x: x[1], reverse=True)[:n]
```

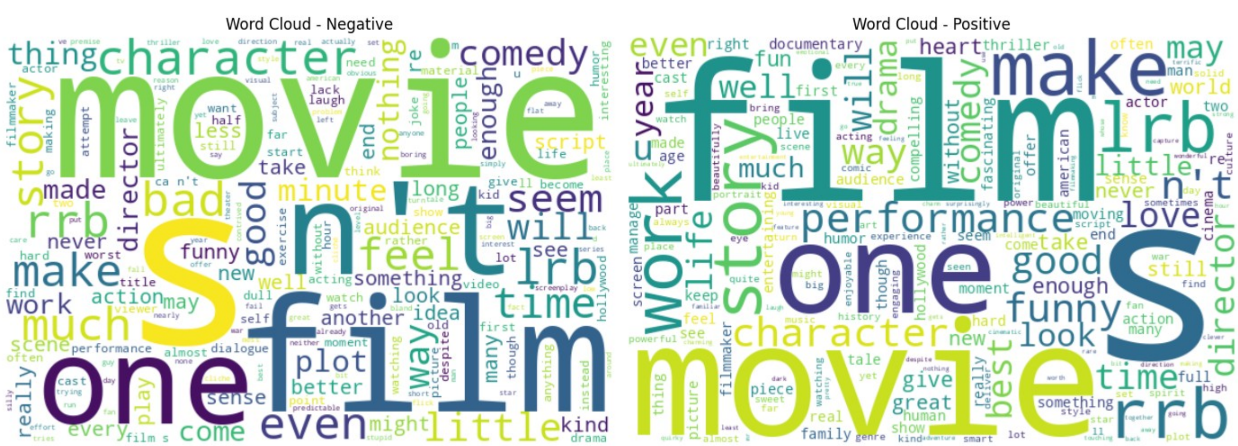
```
print("\nTop 10 Bigrams (Negative Reviews):")
print(get_top_ngrams(df_train[df_train['label']==0]['cleaned_text'],
n=10))

print("\nTop 10 Bigrams (Positive Reviews):")
print(get_top_ngrams(df_train[df_train['label']==1]['cleaned_text'],
n=10))
```




```
Label Proportions:

Train Set:
 label
1    0.521676
0    0.478324
Name: proportion, dtype: float64

Test Set:
 label
0    0.500824
1    0.499176
Name: proportion, dtype: float64
```




```
□ Shortest Train Review:
 why ?

□ Longest Train Review:
 there are n't too many films that can be as simultaneously funny ,
offbeat and heartwarming -lrb- without a thick shmear of the goo , at
least -rrb- , but `` elling '' manages to do all three quite well ,
making it one of the year 's most enjoyable releases .

□ Shortest Test Review:
 ridiculous .

□ Longest Test Review:
 the film is faithful to what one presumes are the book 's twin
premises -- that we become who we are on the backs of our parents ,
but we have no idea who they were at our age ; and that time is a
fleeting and precious commodity no matter how old you are .
```



```
Top 10 Bigrams (Negative Reviews):
[('lrb rrb', np.int64(30)), ('feels like', np.int64(24)), ('plays
like', np.int64(22)), ('romantic comedy', np.int64(18)), ('soap
opera', np.int64(17)), ('ve seen', np.int64(15)), ('writer director',
np.int64(15)), ('running time', np.int64(14)), ('bad movie',
np.int64(13)), ('sci fi', np.int64(12))]

Top 10 Bigrams (Positive Reviews):
[('romantic comedy', np.int64(21)), ('writer director', np.int64(20)),
('lrb rrb', np.int64(20)), ('old fashioned', np.int64(19)), ('coming
age', np.int64(19)), ('ve seen', np.int64(17)), ('good time',
np.int64(16)), ('love story', np.int64(15)), ('subject matter',
np.int64(13)), ('thought provoking', np.int64(11))]
```

##Preprocess Text (cleaning + TF-IDF)

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

# Clean-up function (minimal for performance)
def clean_text(text):
    return text.lower()

df_train['cleaned_text'] = df_train['text'].apply(clean_text)
df_test['cleaned_text'] = df_test['text'].apply(clean_text)

# TF-IDF Vectorization
tfidf = TfidfVectorizer(max_features=5000, stop_words='english')
X = tfidf.fit_transform(df_train['cleaned_text'])
y = df_train['label']
X_test_final = tfidf.transform(df_test['cleaned_text'])
y_test_final = df_test['label']
```

##Train/Validation Split + 10-Fold Cross-Validation

```
from sklearn.model_selection import cross_val_score, train_test_split

# Split train into training and validation (80/20)
X_train, X_val, y_train, y_val = train_test_split(X, y, test_size=0.2,
stratify=y, random_state=42)

# Function to perform 10-fold CV and return average score
def evaluate_model_cv(model, X, y):
    scores = cross_val_score(model, X, y, cv=10, scoring='f1')
    print(f"10-Fold CV F1 Score: {scores.mean():.4f} (+/-
{scores.std():.4f})")
    return scores
```

##Train 5 Models

```python
from sklearn.svm import LinearSVC

svm_model = LinearSVC()
evaluate_model_cv(svm_model, X_train, y_train)
svm_model.fit(X_train, y_train)
```

```
10-Fold CV F1 Score: 0.7686 (+/- 0.0199)
```

```
LinearSVC()
```

```python
from sklearn.neighbors import KNeighborsClassifier

knn_model = KNeighborsClassifier(n_neighbors=5)
evaluate_model_cv(knn_model, X_train, y_train)
knn_model.fit(X_train, y_train)
```

```
10-Fold CV F1 Score: 0.3605 (+/- 0.0365)
```

```
KNeighborsClassifier()
```

```python
from sklearn.tree import DecisionTreeClassifier

dt_model = DecisionTreeClassifier(random_state=42)
evaluate_model_cv(dt_model, X_train, y_train)
dt_model.fit(X_train, y_train)
```

```
10-Fold CV F1 Score: 0.6469 (+/- 0.0260)
```

```
DecisionTreeClassifier(random_state=42)
```

```python
from sklearn.ensemble import RandomForestClassifier

rf_model = RandomForestClassifier(n_estimators=100, random_state=42)
evaluate_model_cv(rf_model, X_train, y_train)
rf_model.fit(X_train, y_train)
```

```
10-Fold CV F1 Score: 0.7238 (+/- 0.0158)
```

```
RandomForestClassifier(random_state=42)
```

```python
import xgboost as xgb

xgb_model = xgb.XGBClassifier(use_label_encoder=False,
eval_metric='logloss', random_state=42)
evaluate_model_cv(xgb_model, X_train, y_train)
xgb_model.fit(X_train, y_train)
```

```
/usr/local/lib/python3.11/dist-packages/xgboost/core.py:158:
UserWarning: [18:16:39] WARNING: /workspace/src/learner.cc:740:
Parameters: { "use_label_encoder" } are not used.
```

```
  warnings.warn(smsg, UserWarning)
/usr/local/lib/python3.11/dist-packages/xgboost/core.py:158:
UserWarning: [18:16:41] WARNING: /workspace/src/learner.cc:740:
Parameters: { "use_label_encoder" } are not used.

  warnings.warn(smsg, UserWarning)
/usr/local/lib/python3.11/dist-packages/xgboost/core.py:158:
UserWarning: [18:16:43] WARNING: /workspace/src/learner.cc:740:
Parameters: { "use_label_encoder" } are not used.

  warnings.warn(smsg, UserWarning)
/usr/local/lib/python3.11/dist-packages/xgboost/core.py:158:
UserWarning: [18:16:46] WARNING: /workspace/src/learner.cc:740:
Parameters: { "use_label_encoder" } are not used.

  warnings.warn(smsg, UserWarning)
/usr/local/lib/python3.11/dist-packages/xgboost/core.py:158:
UserWarning: [18:16:48] WARNING: /workspace/src/learner.cc:740:
Parameters: { "use_label_encoder" } are not used.

  warnings.warn(smsg, UserWarning)
/usr/local/lib/python3.11/dist-packages/xgboost/core.py:158:
UserWarning: [18:16:49] WARNING: /workspace/src/learner.cc:740:
Parameters: { "use_label_encoder" } are not used.

  warnings.warn(smsg, UserWarning)
/usr/local/lib/python3.11/dist-packages/xgboost/core.py:158:
UserWarning: [18:16:51] WARNING: /workspace/src/learner.cc:740:
Parameters: { "use_label_encoder" } are not used.

  warnings.warn(smsg, UserWarning)
/usr/local/lib/python3.11/dist-packages/xgboost/core.py:158:
UserWarning: [18:16:53] WARNING: /workspace/src/learner.cc:740:
Parameters: { "use_label_encoder" } are not used.

  warnings.warn(smsg, UserWarning)
/usr/local/lib/python3.11/dist-packages/xgboost/core.py:158:
UserWarning: [18:16:54] WARNING: /workspace/src/learner.cc:740:
Parameters: { "use_label_encoder" } are not used.

  warnings.warn(smsg, UserWarning)
/usr/local/lib/python3.11/dist-packages/xgboost/core.py:158:
UserWarning: [18:16:56] WARNING: /workspace/src/learner.cc:740:
Parameters: { "use_label_encoder" } are not used.

  warnings.warn(smsg, UserWarning)

10-Fold CV F1 Score: 0.7059 (+/- 0.0273)

/usr/local/lib/python3.11/dist-packages/xgboost/core.py:158:
UserWarning: [18:16:59] WARNING: /workspace/src/learner.cc:740:
```

```
Parameters: { "use_label_encoder" } are not used.

  warnings.warn(smsg, UserWarning)

XGBClassifier(base_score=None, booster=None, callbacks=None,
              colsample_bylevel=None, colsample_bynode=None,
              colsample_bytree=None, device=None,
early_stopping_rounds=None,
              enable_categorical=False, eval_metric='logloss',
              feature_types=None, gamma=None, grow_policy=None,
              importance_type=None, interaction_constraints=None,
              learning_rate=None, max_bin=None,
max_cat_threshold=None,
              max_cat_to_onehot=None, max_delta_step=None,
max_depth=None,
              max_leaves=None, min_child_weight=None, missing=nan,
              monotone_constraints=None, multi_strategy=None,
n_estimators=None,
              n_jobs=None, num_parallel_tree=None,
random_state=42, ...)
```

##Final Evaluation on Test Set

```
from sklearn.metrics import accuracy_score, precision_score,
recall_score, f1_score, classification_report, confusion_matrix

def evaluate_final(model, X_test, y_test, name="Model"):
    preds = model.predict(X_test)
    print(f"□ {name} Evaluation on Test Set:")
    print("Accuracy:", accuracy_score(y_test, preds))
    print("Precision:", precision_score(y_test, preds))
    print("Recall:", recall_score(y_test, preds))
    print("F1 Score:", f1_score(y_test, preds))
    print("\nConfusion Matrix:\n", confusion_matrix(y_test, preds))
    print("-" * 50)

# Evaluate all
evaluate_final(svm_model, X_test_final, y_test_final, "SVM")
evaluate_final(knn_model, X_test_final, y_test_final, "KNN")
evaluate_final(dt_model, X_test_final, y_test_final, "Decision Tree")
evaluate_final(rf_model, X_test_final, y_test_final, "Random Forest")
evaluate_final(xgb_model, X_test_final, y_test_final, "XGBoost")

□ SVM Evaluation on Test Set:
Accuracy: 0.7726523887973641
Precision: 0.7591623036649214
Recall: 0.7975797579757976
F1 Score: 0.7778969957081545

Confusion Matrix:
```

```
 [[682 230]
 [184 725]]
--------------------------------------------------
□ KNN Evaluation on Test Set:
Accuracy: 0.515650741350906
Precision: 0.5266272189349113
Recall: 0.29372937293729373
F1 Score: 0.3771186440677966

Confusion Matrix:
 [[672 240]
 [642 267]]
--------------------------------------------------
□ Decision Tree Evaluation on Test Set:
Accuracy: 0.6732564524986271
Precision: 0.6713973799126638
Recall: 0.6765676567656765
F1 Score: 0.673972602739726

Confusion Matrix:
 [[611 301]
 [294 615]]
--------------------------------------------------
□ Random Forest Evaluation on Test Set:
Accuracy: 0.7353102690829215
Precision: 0.7468208092485549
Recall: 0.7106710671067107
F1 Score: 0.7282976324689966

Confusion Matrix:
 [[693 219]
 [263 646]]
--------------------------------------------------
□ XGBoost Evaluation on Test Set:
Accuracy: 0.6825919824272377
Precision: 0.6497737556561086
Recall: 0.7898789878987899
F1 Score: 0.7130089374379345

Confusion Matrix:
 [[525 387]
 [191 718]]
--------------------------------------------------
```

Question 3 (30 Points)

Text Clustering

The purpose of the question is to practice different machine learning algorithms for **text clustering**.

Please downlad the dataset by using the following link.
https://www.kaggle.com/PromptCloudHQ/amazon-reviews-unlocked-mobile-phones (You can also use different text data which you want)

1. Perform EDA on selected dataset

2. **Apply the listed clustering methods (Any 4) to the dataset:**

- K-means
- DBSCAN
- Hierarchical clustering
- Word2Vec
- BERT

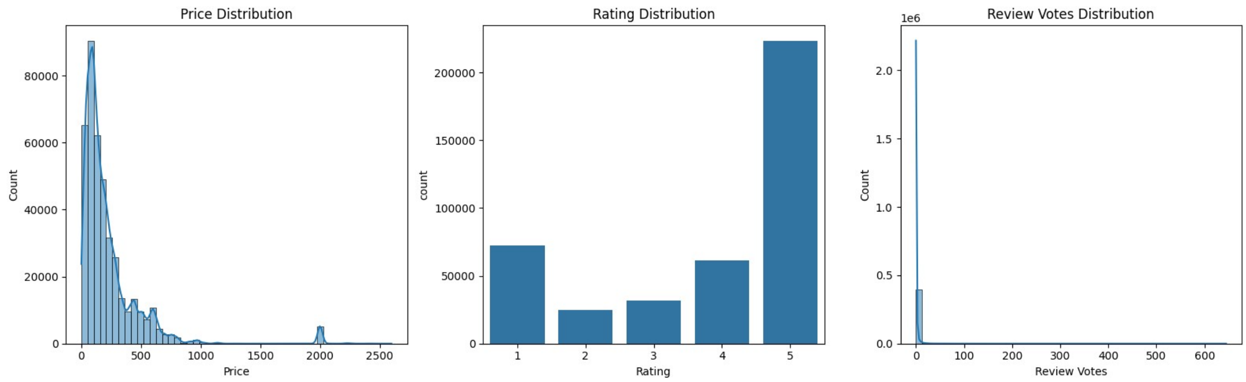
1. **Visualize the clusters**

You can refer to of the codes from the follwing link below.
https://www.kaggle.com/karthik3890/text-clustering

```
 #Required Libraries
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns

# Load the dataset
df = pd.read_csv("/content/Amazon_Unlocked_Mobile.csv")

# EDA
df.info()
print("\nMissing Values:\n", df.isnull().sum())
print("\nSummary Stats:\n", df.describe())

# Fill missing reviews for clustering
df['Reviews'] = df['Reviews'].fillna('').str.lower()

# Plot Distributions
plt.figure(figsize=(16, 5))
plt.subplot(1, 3, 1)
sns.histplot(df['Price'].dropna(), bins=50, kde=True)
plt.title('Price Distribution')

plt.subplot(1, 3, 2)
```

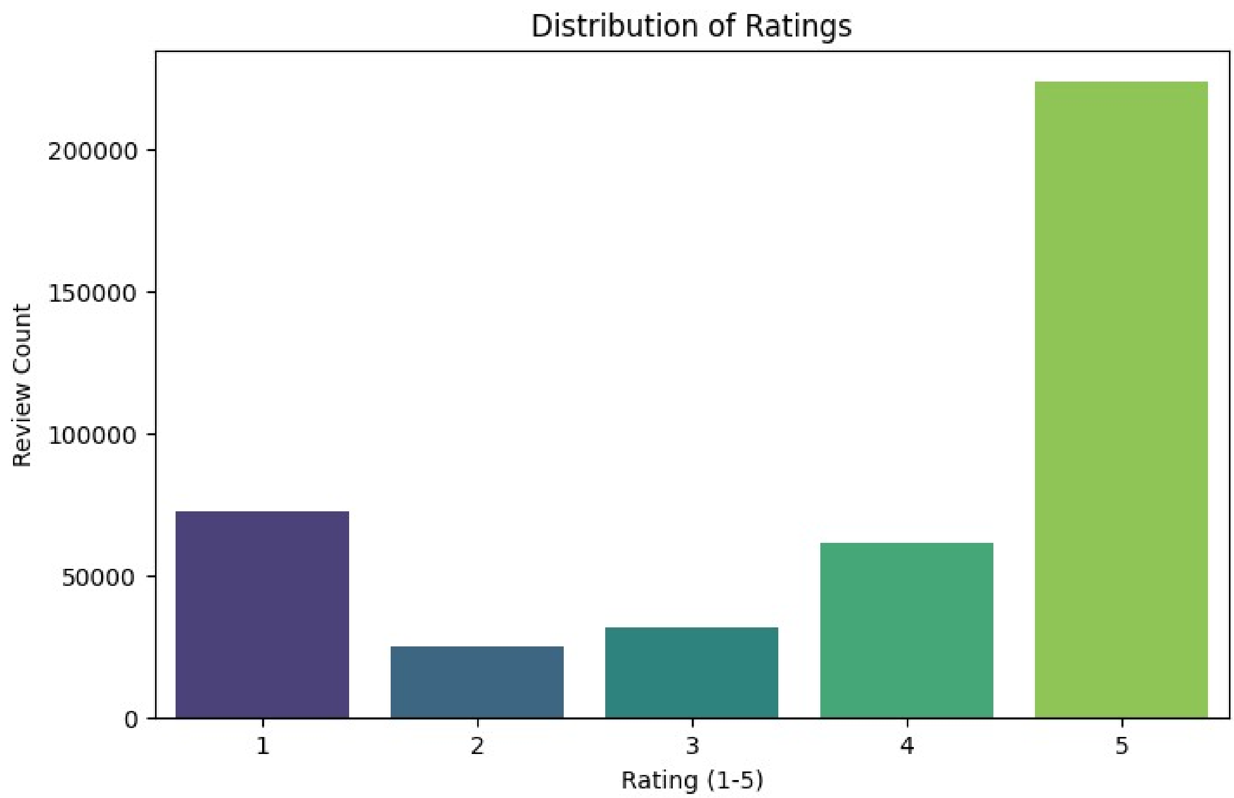
```python
sns.countplot(x='Rating', data=df)
plt.title('Rating Distribution')

plt.subplot(1, 3, 3)
sns.histplot(df['Review Votes'].dropna(), bins=50, kde=True)
plt.title('Review Votes Distribution')
plt.tight_layout()
plt.show()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 413840 entries, 0 to 413839
Data columns (total 6 columns):
 #   Column         Non-Null Count   Dtype
---  ------         --------------   -----
 0   Product Name   413840 non-null  object
 1   Brand Name     348669 non-null  object
 2   Price          407907 non-null  float64
 3   Rating         413840 non-null  int64
 4   Reviews        413770 non-null  object
 5   Review Votes   401544 non-null  float64
dtypes: float64(2), int64(1), object(3)
memory usage: 18.9+ MB

Missing Values:
 Product Name        0
Brand Name      65171
Price            5933
Rating              0
Reviews            70
Review Votes    12296
dtype: int64

Summary Stats:
                Price         Rating   Review Votes
count  407907.000000  413840.000000  401544.000000
mean      226.867155       3.819578       1.507237
std       273.006259       1.548216       9.163853
min         1.730000       1.000000       0.000000
25%        79.990000       3.000000       0.000000
50%       144.710000       5.000000       0.000000
75%       269.990000       5.000000       1.000000
max      2598.000000       5.000000     645.000000
```

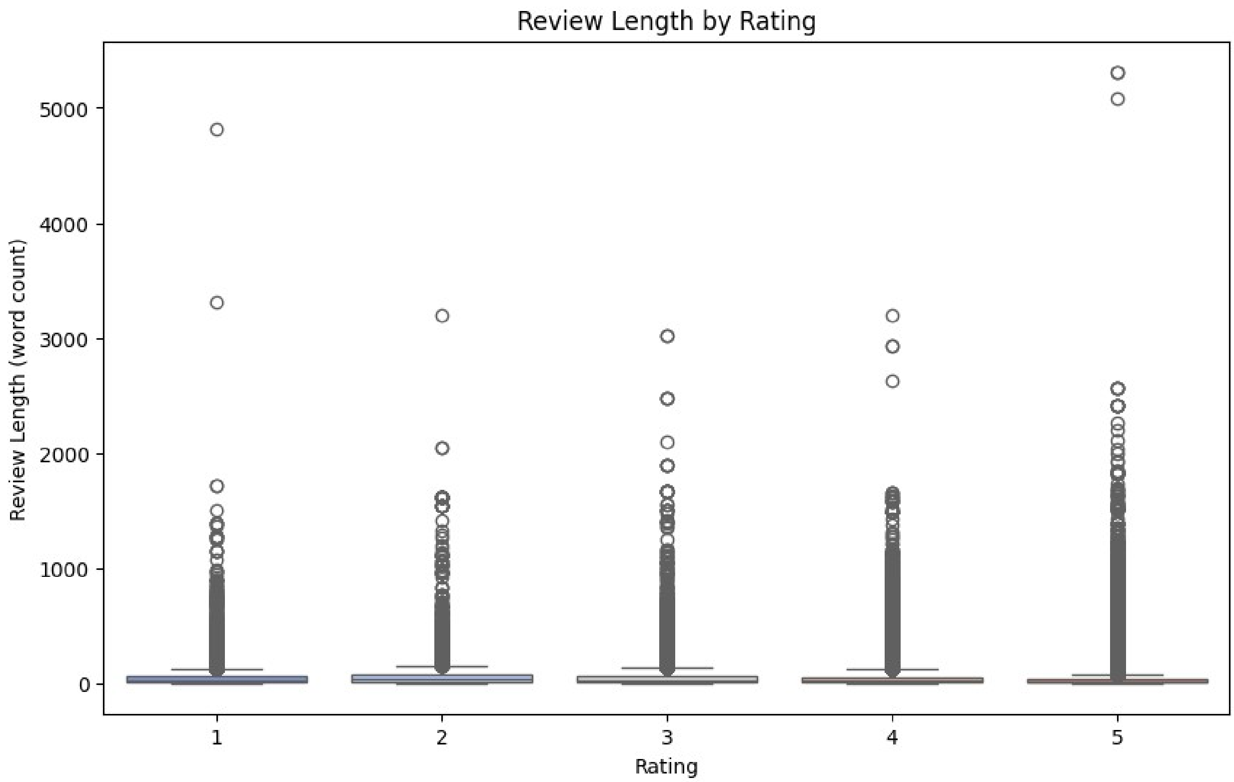



```
if 'Rating' in df.columns:
    plt.figure(figsize=(8, 5))
    sns.countplot(x='Rating', data=df, palette='viridis')
    plt.title("Distribution of Ratings")
    plt.xlabel("Rating (1-5)")
    plt.ylabel("Review Count")
    plt.show()
```

```
<ipython-input-4-f5181f0332d7>:3: FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be
removed in v0.14.0. Assign the `x` variable to `hue` and set
`legend=False` for the same effect.

  sns.countplot(x='Rating', data=df, palette='viridis')
```



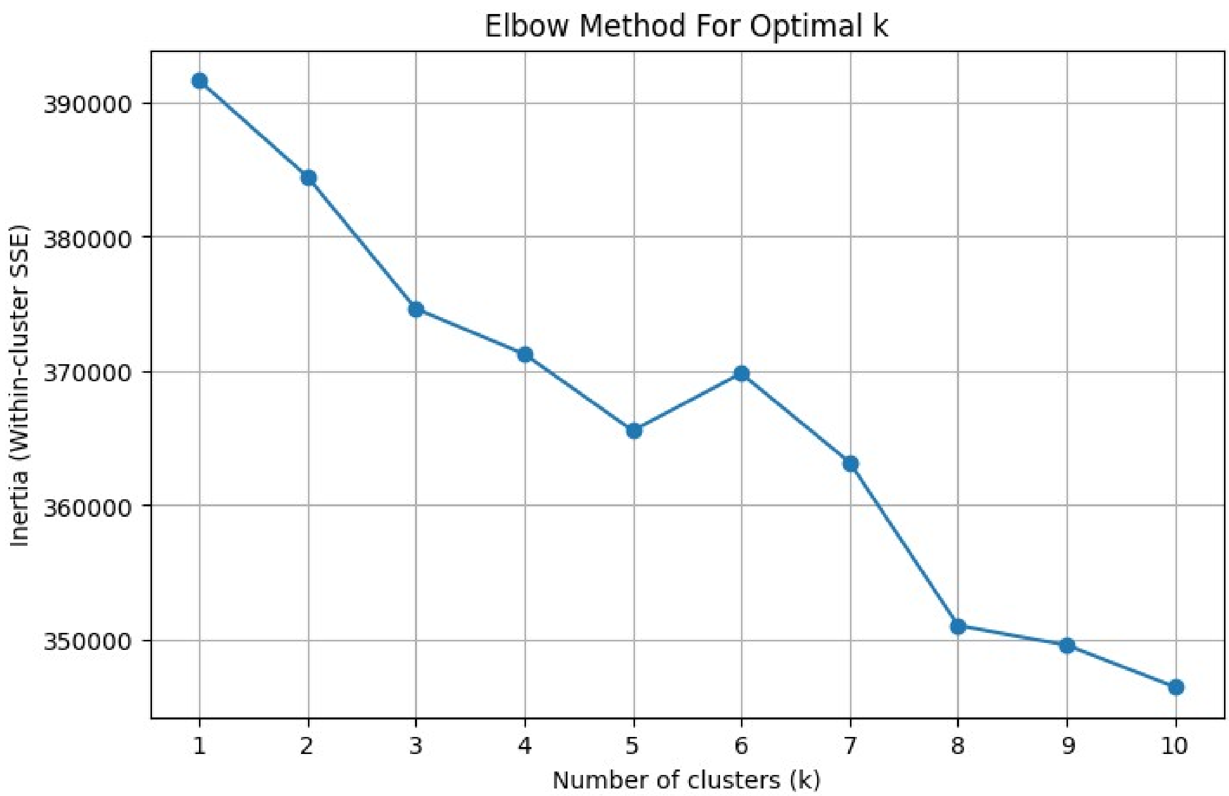

```
if 'Rating' in df.columns:
    df['review_length'] = df['Reviews'].apply(lambda x:
len(x.split()))  # Calculate review length
    plt.figure(figsize=(10, 6))
    sns.boxplot(x='Rating', y='review_length', data=df,
palette='coolwarm')
    plt.title("Review Length by Rating")
    plt.xlabel("Rating")
    plt.ylabel("Review Length (word count)")
    plt.show()

<ipython-input-6-90630dbed88b>:4: FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be
removed in v0.14.0. Assign the `x` variable to `hue` and set
`legend=False` for the same effect.

  sns.boxplot(x='Rating', y='review_length', data=df,
palette='coolwarm')
```



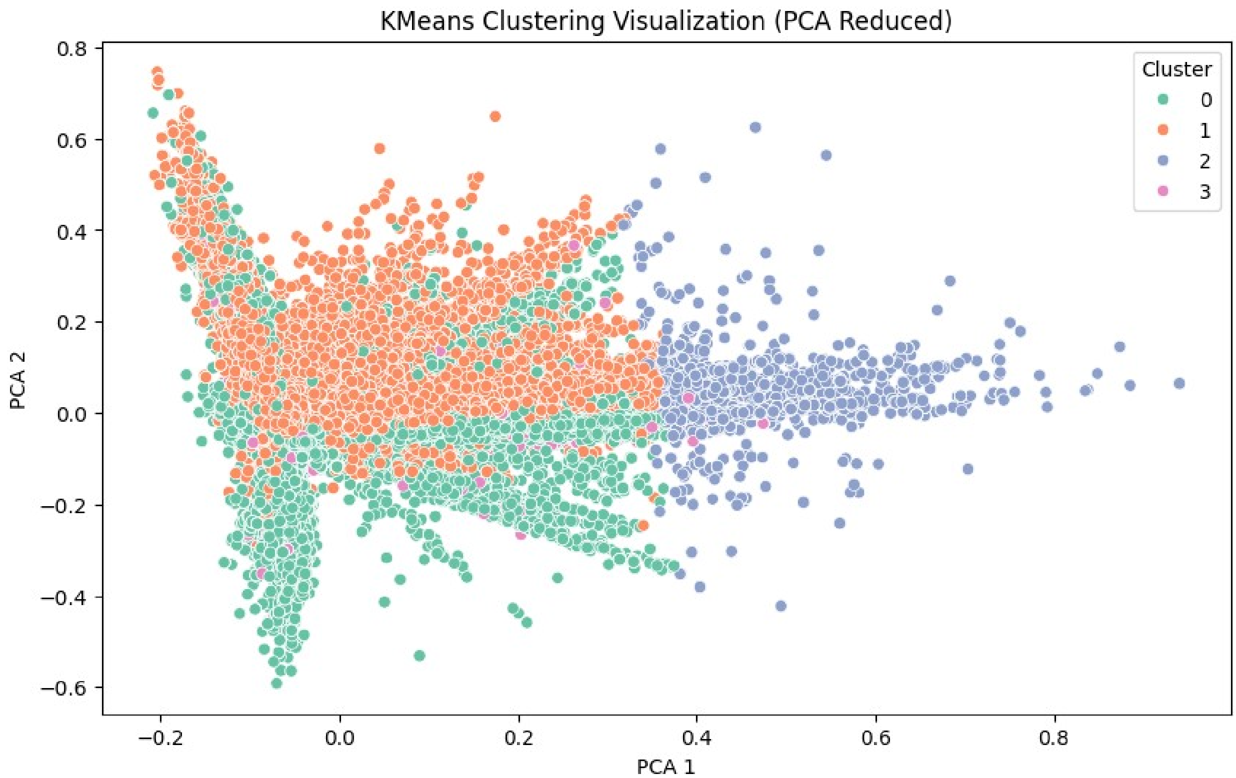

```
import nltk
from nltk.corpus import stopwords
#from nltk.stem import PorterStemmer
from nltk.stem import WordNetLemmatizer
import re # Import the 're' module for regular expressions

nltk.download('wordnet')

nltk.download('stopwords')
stop_words = set(stopwords.words('english'))
#stemmer = PorterStemmer()
lemmatizer = WordNetLemmatizer()

def preprocess(text):
    text = re.sub(r'[^a-zA-Z]', ' ', str(text))
    words = text.lower().split()
    words = [lemmatizer.lemmatize(w) for w in words if w not in
stop_words]
    return ' '.join(words)

df['cleaned_reviews'] = df['Reviews'].apply(preprocess)
```

```
[nltk_data] Downloading package wordnet to /root/nltk_data...
[nltk_data]   Package wordnet is already up-to-date!
[nltk_data] Downloading package stopwords to /root/nltk_data...
[nltk_data]   Package stopwords is already up-to-date!
```

```python
from sklearn.feature_extraction.text import TfidfVectorizer

vectorizer = TfidfVectorizer(max_features=1000)
X_tfidf = vectorizer.fit_transform(df['cleaned_reviews'])

from sklearn.cluster import KMeans
import matplotlib.pyplot as plt

# Run KMeans for a range of cluster numbers and calculate inertia
inertias = []
k_range = range(1, 11)

for k in k_range:
    kmeans = KMeans(n_clusters=k, random_state=42)
    kmeans.fit(X_tfidf)
    inertias.append(kmeans.inertia_)

# Plotting the Elbow Curve
plt.figure(figsize=(8, 5))
plt.plot(k_range, inertias, marker='o')
plt.title('Elbow Method For Optimal k')
plt.xlabel('Number of clusters (k)')
plt.ylabel('Inertia (Within-cluster SSE)')
plt.xticks(k_range)
plt.grid(True)
plt.show()
```

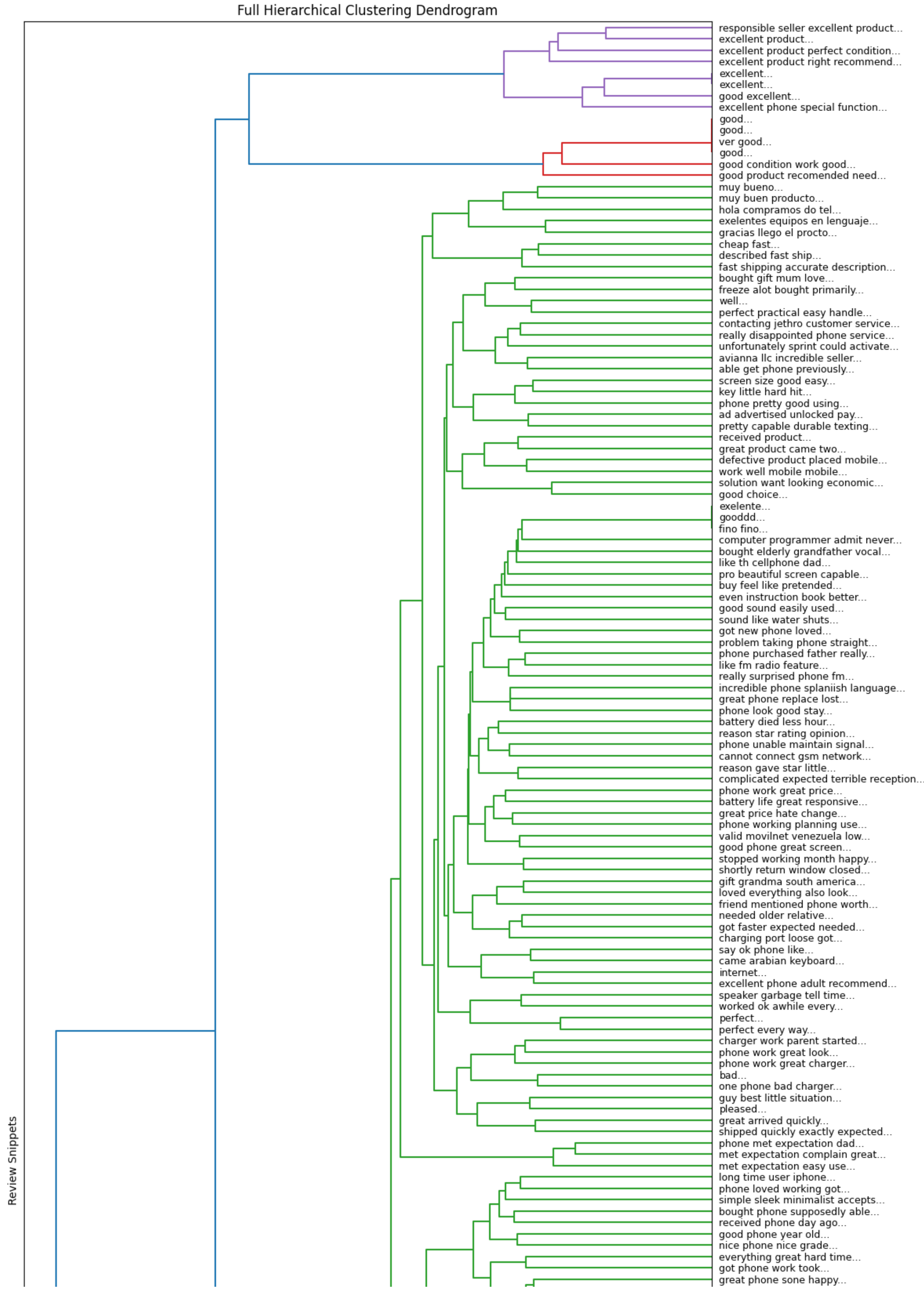



```
from sklearn.cluster import KMeans

kmeans = KMeans(n_clusters=4, random_state=42)
kmeans_labels = kmeans.fit_predict(X_tfidf)
df['KMeans_Cluster'] = kmeans_labels

df['KMeans_Cluster'].unique()

array([1, 0, 2, 3], dtype=int32)

from sklearn.decomposition import PCA
import seaborn as sns

# Reduce dimensions for visualization
pca = PCA(n_components=2)
X_reduced = pca.fit_transform(X_tfidf.toarray())

# Plot the clusters
plt.figure(figsize=(10, 6))
sns.scatterplot(x=X_reduced[:, 0], y=X_reduced[:, 1],
hue=df['KMeans_Cluster'], palette='Set2')
plt.title("KMeans Clustering Visualization (PCA Reduced)")
plt.xlabel("PCA 1")
plt.ylabel("PCA 2")
plt.legend(title='Cluster')
plt.show()
```




```
from scipy.cluster.hierarchy import dendrogram, linkage
import matplotlib.pyplot as plt

# Use only a subset of reviews and their text (for visualization)
subset_size = 200  # You can adjust based on clarity
subset_texts = df['cleaned_reviews'].iloc[:subset_size]
subset_features = X_tfidf.toarray()[:subset_size]

# Create linkage matrix
linkage_matrix = linkage(subset_features, method='ward')

# Generate review labels (e.g., first 3-5 words of each review)
labels = [' '.join(review.split()[:4]) + '...' for review in
subset_texts]

# Plot vertical dendrogram with labels
plt.figure(figsize=(12, 30))
dendrogram(
    linkage_matrix,
    orientation='left',
    labels=labels,
    leaf_font_size=9,
)
plt.title("Full Hierarchical Clustering Dendrogram")
plt.xlabel("Distance")
plt.ylabel("Review Snippets")
```

```
plt.tight_layout()
plt.show()
```


Full Hierarchical Clustering Dendrogram
Review Snippets
responsible seller excellent product...
excellent product...
excellent product perfect condition...
excellent product right recommend...
excellent...
excellent...
good excellent...
excellent phone special function...
good...
good...
ver good...
good...
good condition work good...
good product recomended need...
muy bueno...
muy buen producto...
hola compramos do tel...
exelentes equipos en lenguaje...
gracias llego el procto...
cheap fast...
described fast ship...
fast shipping accurate description...
bought gift mum love...
freeze alot bought primarily...
well...
perfect practical easy handle...
contacting jethro customer service...
really disappointed phone service...
unfortunately sprint could activate...
avianna llc incredible seller...
able get phone previously...
screen size good easy...
key little hard hit...
phone pretty good using...
ad advertised unlocked pay...
pretty capable durable texting...
received product...
great product came two...
defective product placed mobile...
work well mobile mobile...
solution want looking economic...
good choice...
exelente...
gooddd...
fino fino...
computer programmer admit never...
bought elderly grandfather vocal...
like th cellphone dad...
pro beautiful screen capable...
buy feel like pretended...
even instruction book better...
good sound easily used...
sound like water shuts...
got new phone loved...
problem taking phone straight...
phone purchased father really...
like fm radio feature...
really surprised phone fm...
incredible phone splaniish language...
great phone replace lost...
phone look good stay...
battery died less hour...
reason star rating opinion...
phone unable maintain signal...
cannot connect gsm network...
reason gave star little...
complicated expected terrible reception...
phone work great price...
battery life great responsive...
great price hate change...
phone working planning use...
valid movilnet venezuela low...
good phone great screen...
stopped working month happy...
shortly return window closed...
gift grandma south america...
loved everything also look...
friend mentioned phone worth...
needed older relative...
got faster expected needed...
charging port loose got...
say ok phone like...
came arabian keyboard...
internet...
excellent phone adult recommend...
speaker garbage tell time...
worked ok awhile every...
perfect...
perfect every way...
charger work parent started...
phone work great look...
phone work great charger...
bad...
one phone bad charger...
guy best little situation...
pleased...
great arrived quickly...
shipped quickly exactly expected...
phone met expectation dad...
met expectation complain great...
met expectation easy use...
long time user iphone...
phone loved working got...
simple sleek minimalist accepts...
bought phone supposedly able...
received phone day ago...
good phone year old...
nice phone nice grade...
everything great hard time...
got phone work took...
great phone sone happy...

```python
from sklearn.feature_extraction.text import TfidfVectorizer
from sklearn.cluster import KMeans
from sklearn.manifold import TSNE

# TF-IDF Vectorization
vectorizer = TfidfVectorizer(max_features=1000, stop_words='english')
tfidf_matrix = vectorizer.fit_transform(df['Reviews'])

# K-Means Clustering
kmeans = KMeans(n_clusters=5, random_state=42)
kmeans_labels = kmeans.fit_predict(tfidf_matrix)

# t-SNE for visualization
tsne = TSNE(n_components=2, random_state=42)
tsne_result = tsne.fit_transform(tfidf_matrix.toarray())

# Plot
plt.figure(figsize=(10, 6))
sns.scatterplot(x=tsne_result[:, 0], y=tsne_result[:, 1],
hue=kmeans_labels, palette='tab10')
plt.title('K-Means Clustering (t-SNE)')
plt.show()

#pip install gensim==4.3.1 numpy==1.23.5
#!pip install gensim==4.3.1 scipy==1.10.1
!pip install --upgrade jax jaxlib
```

```
Requirement already satisfied: jax in /usr/local/lib/python3.11/dist-
packages (0.5.2)
Collecting jax
  Downloading jax-0.6.0-py3-none-any.whl.metadata (22 kB)
Requirement already satisfied: jaxlib in
/usr/local/lib/python3.11/dist-packages (0.5.1)
Collecting jaxlib
  Downloading jaxlib-0.6.0-cp311-cp311-
manylinux2014_x86_64.whl.metadata (1.2 kB)
Collecting ml_dtypes>=0.5.0 (from jax)
  Downloading ml_dtypes-0.5.1-cp311-cp311-
manylinux_2_17_x86_64.manylinux2014_x86_64.whl.metadata (21 kB)
Requirement already satisfied: numpy>=1.25 in
/usr/local/lib/python3.11/dist-packages (from jax) (2.0.2)
Requirement already satisfied: opt_einsum in
/usr/local/lib/python3.11/dist-packages (from jax) (3.4.0)
Requirement already satisfied: scipy>=1.11.1 in
/usr/local/lib/python3.11/dist-packages (from jax) (1.14.1)
Downloading jax-0.6.0-py3-none-any.whl (2.3 MB)
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0:00:00
anylinux2014_x86_64.whl (87.8 MB)
```

```
━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 87.8/87.8 MB 9.0 MB/s eta
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l_dtypes-0.5.1-cp311-cp311-
manylinux_2_17_x86_64.manylinux2014_x86_64.whl (4.7 MB)
━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 4.7/4.7 MB 58.2 MB/s eta
0:00:00
l_dtypes, jaxlib, jax
  Attempting uninstall: ml_dtypes
    Found existing installation: ml-dtypes 0.4.1
    Uninstalling ml-dtypes-0.4.1:
      Successfully uninstalled ml-dtypes-0.4.1
  Attempting uninstall: jaxlib
    Found existing installation: jaxlib 0.5.1
    Uninstalling jaxlib-0.5.1:
      Successfully uninstalled jaxlib-0.5.1
  Attempting uninstall: jax
    Found existing installation: jax 0.5.2
    Uninstalling jax-0.5.2:
      Successfully uninstalled jax-0.5.2
ERROR: pip's dependency resolver does not currently take into account
all the packages that are installed. This behaviour is the source of
the following dependency conflicts.
tensorflow 2.18.0 requires ml-dtypes<0.5.0,>=0.4.0, but you have ml-
dtypes 0.5.1 which is incompatible.
Successfully installed jax-0.6.0 jaxlib-0.6.0 ml_dtypes-0.5.1
```

```
!pip uninstall -y gensim scipy
!pip install gensim==4.3.1 scipy==1.10.1
```

```
WARNING: Skipping gensim as it is not installed.
Found existing installation: scipy 1.14.1
Uninstalling scipy-1.14.1:
  Successfully uninstalled scipy-1.14.1
Collecting gensim==4.3.1
  Downloading gensim-4.3.1-cp311-cp311-
manylinux_2_17_x86_64.manylinux2014_x86_64.whl.metadata (8.4 kB)
Collecting scipy==1.10.1
  Downloading scipy-1.10.1-cp311-cp311-
manylinux_2_17_x86_64.manylinux2014_x86_64.whl.metadata (58 kB)
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0:00:00
ent already satisfied: numpy>=1.18.5 in
/usr/local/lib/python3.11/dist-packages (from gensim==4.3.1) (2.0.2)
Requirement already satisfied: smart-open>=1.8.1 in
/usr/local/lib/python3.11/dist-packages (from gensim==4.3.1) (7.1.0)
Collecting numpy>=1.18.5 (from gensim==4.3.1)
  Downloading numpy-1.26.4-cp311-cp311-
manylinux_2_17_x86_64.manylinux2014_x86_64.whl.metadata (61 kB)
━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 61.0/61.0 kB 2.5 MB/s eta
0:00:00
```

```
ent already satisfied: wrapt in /usr/local/lib/python3.11/dist-
packages (from smart-open>=1.8.1->gensim==4.3.1) (1.17.2)
Downloading gensim-4.3.1-cp311-cp311-
manylinux_2_17_x86_64.manylinux2014_x86_64.whl (26.6 MB)
━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 26.6/26.6 MB 27.4 MB/s eta
0:00:00
anylinux_2_17_x86_64.manylinux2014_x86_64.whl (34.1 MB)
━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 34.1/34.1 MB 26.1 MB/s eta
0:00:00
py-1.26.4-cp311-cp311-manylinux_2_17_x86_64.manylinux2014_x86_64.whl
(18.3 MB)
━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 18.3/18.3 MB 88.8 MB/s eta
0:00:00
py, scipy, gensim
  Attempting uninstall: numpy
    Found existing installation: numpy 2.0.2
    Uninstalling numpy-2.0.2:
      Successfully uninstalled numpy-2.0.2
ERROR: pip's dependency resolver does not currently take into account
all the packages that are installed. This behaviour is the source of
the following dependency conflicts.
jax 0.6.0 requires scipy>=1.11.1, but you have scipy 1.10.1 which is
incompatible.
jaxlib 0.6.0 requires scipy>=1.11.1, but you have scipy 1.10.1 which
is incompatible.
thinc 8.3.6 requires numpy<3.0.0,>=2.0.0, but you have numpy 1.26.4
which is incompatible.
cvxpy 1.6.5 requires scipy>=1.11.0, but you have scipy 1.10.1 which is
incompatible.
scikit-image 0.25.2 requires scipy>=1.11.4, but you have scipy 1.10.1
which is incompatible.
tensorflow 2.18.0 requires ml-dtypes<0.5.0,>=0.4.0, but you have ml-
dtypes 0.5.1 which is incompatible.
Successfully installed gensim-4.3.1 numpy-1.26.4 scipy-1.10.1
```

```
!pip install --upgrade scipy
```

```
Requirement already satisfied: scipy in
/usr/local/lib/python3.11/dist-packages (1.15.2)
Requirement already satisfied: numpy<2.5,>=1.23.5 in
/usr/local/lib/python3.11/dist-packages (from scipy) (1.26.4)
```

```
# Fix scipy compatibility with gensim
!pip install -U "scipy<1.11.0"
```

```
Collecting scipy<1.11.0
  Using cached scipy-1.10.1-cp311-cp311-
manylinux_2_17_x86_64.manylinux2014_x86_64.whl.metadata (58 kB)
Requirement already satisfied: numpy<1.27.0,>=1.19.5 in
/usr/local/lib/python3.11/dist-packages (from scipy<1.11.0) (1.26.4)
```

```
Using cached scipy-1.10.1-cp311-cp311-
manylinux_2_17_x86_64.manylinux2014_x86_64.whl (34.1 MB)
Installing collected packages: scipy
  Attempting uninstall: scipy
    Found existing installation: scipy 1.15.2
    Uninstalling scipy-1.15.2:
      Successfully uninstalled scipy-1.15.2
ERROR: pip's dependency resolver does not currently take into account
all the packages that are installed. This behaviour is the source of
the following dependency conflicts.
jax 0.6.0 requires scipy>=1.11.1, but you have scipy 1.10.1 which is
incompatible.
jaxlib 0.6.0 requires scipy>=1.11.1, but you have scipy 1.10.1 which
is incompatible.
cvxpy 1.6.5 requires scipy>=1.11.0, but you have scipy 1.10.1 which is
incompatible.
scikit-image 0.25.2 requires scipy>=1.11.4, but you have scipy 1.10.1
which is incompatible.
Successfully installed scipy-1.10.1
```

```python
from gensim.models import Word2Vec
from nltk.tokenize import word_tokenize
import nltk

nltk.download('punkt')  # Correct model for tokenizing
```

```
[nltk_data] Downloading package punkt to /root/nltk_data...
[nltk_data]   Unzipping tokenizers/punkt.zip.
```

```
True
```

```python
import nltk
nltk.download('punkt_tab')
from gensim.models import Word2Vec
from nltk.tokenize import word_tokenize
nltk.download('punkt')
import numpy as np
from nltk.corpus import stopwords
from nltk.stem import WordNetLemmatizer
import re # Import the 're' module for regular expressions

nltk.download('wordnet')
nltk.download('stopwords')
stop_words = set(stopwords.words('english'))
#stemmer = PorterStemmer()
lemmatizer = WordNetLemmatizer()


def preprocess(text):
    text = re.sub(r'[^a-zA-Z]', ' ', str(text))
    words = text.lower().split()
```

```
    words = [lemmatizer.lemmatize(w) for w in words if w not in
stop_words]
    return ' '.join(words)

# Create the cleaned_reviews column before using it
df['cleaned_reviews'] = df['Reviews'].apply(preprocess)

tokenized_reviews = df['cleaned_reviews'].apply(word_tokenize)
w2v_model = Word2Vec(sentences=tokenized_reviews, vector_size=100,
window=5, min_count=1)

# Average word vectors per review
def get_avg_vector(tokens):
    vectors = [w2v_model.wv[word] for word in tokens if word in
w2v_model.wv]
    return np.mean(vectors, axis=0) if vectors else np.zeros(100)

X_w2v = np.vstack(df['cleaned_reviews'].apply(lambda x:
get_avg_vector(word_tokenize(x))))
kmeans_w2v = KMeans(n_clusters=4, random_state=42).fit(X_w2v)
df['W2V_Cluster'] = kmeans_w2v.labels_
```

```
[nltk_data] Downloading package punkt_tab to /root/nltk_data...
[nltk_data]   Package punkt_tab is already up-to-date!
[nltk_data] Downloading package punkt to /root/nltk_data...
[nltk_data]   Package punkt is already up-to-date!
[nltk_data] Downloading package wordnet to /root/nltk_data...
[nltk_data]   Package wordnet is already up-to-date!
[nltk_data] Downloading package stopwords to /root/nltk_data...
[nltk_data]   Package stopwords is already up-to-date!
```

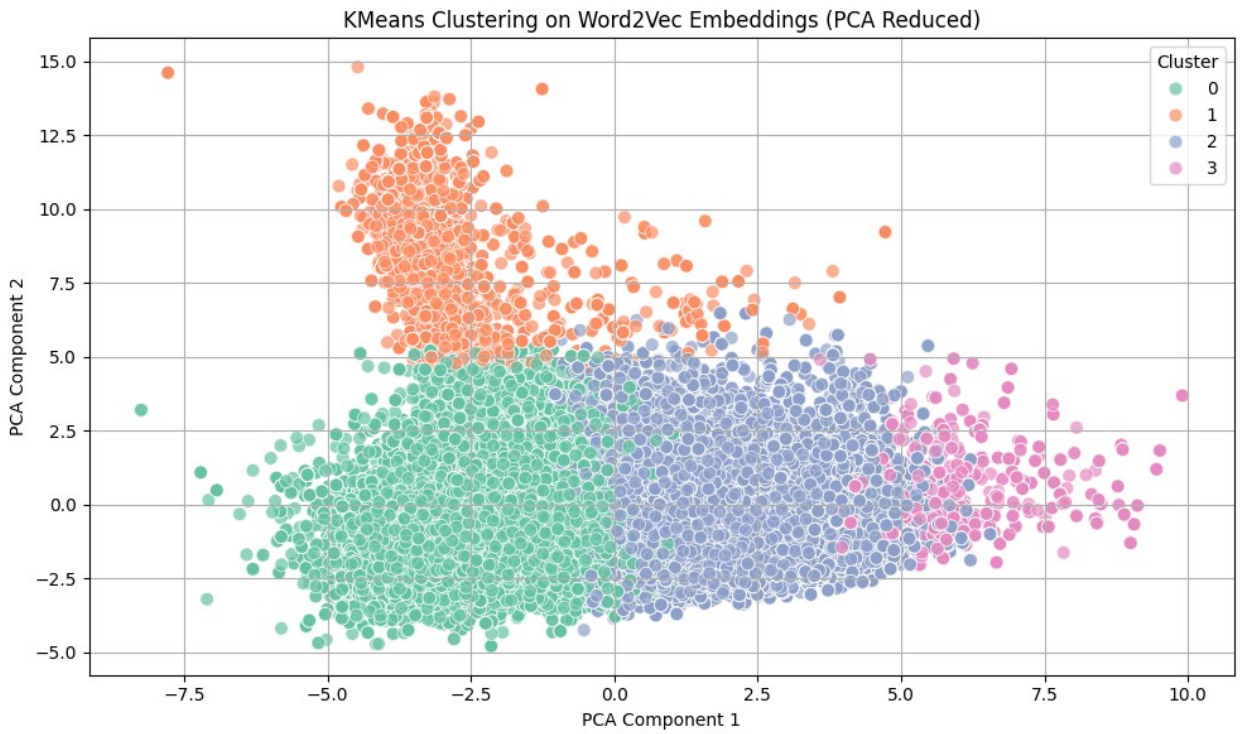
```
from sklearn.decomposition import PCA
import matplotlib.pyplot as plt
import seaborn as sns

# Reduce Word2Vec vectors to 2D using PCA
pca = PCA(n_components=2)
X_w2v_pca = pca.fit_transform(X_w2v)

# Add PCA components to DataFrame
df['W2V_PCA1'] = X_w2v_pca[:, 0]
df['W2V_PCA2'] = X_w2v_pca[:, 1]

# Plot clusters
plt.figure(figsize=(10, 6))
sns.scatterplot(
    data=df, x='W2V_PCA1', y='W2V_PCA2',
    hue='W2V_Cluster', palette='Set2', s=60, alpha=0.7
)
plt.title("KMeans Clustering on Word2Vec Embeddings (PCA Reduced)")
```

```
plt.xlabel("PCA Component 1")
plt.ylabel("PCA Component 2")
plt.legend(title="Cluster", loc="best")
plt.grid(True)
plt.tight_layout()
plt.show()
```




```
from sklearn.feature_extraction.text import TfidfVectorizer # Import
TfidfVectorizer

sampled_df = df.sample(n=50000, random_state=42).copy()

vectorizer = TfidfVectorizer(max_features=1000, stop_words='english')
# Initialize TfidfVectorizer
X_sampled_tfidf =
vectorizer.fit_transform(sampled_df['cleaned_reviews'])

from sklearn.cluster import DBSCAN

dbscan = DBSCAN(eps=0.4, min_samples=20, metric='cosine')
dbscan_labels = dbscan.fit_predict(X_sampled_tfidf)

sampled_df['DBSCAN_Cluster'] = dbscan_labels

sampled_df['DBSCAN_Cluster'].unique()
```

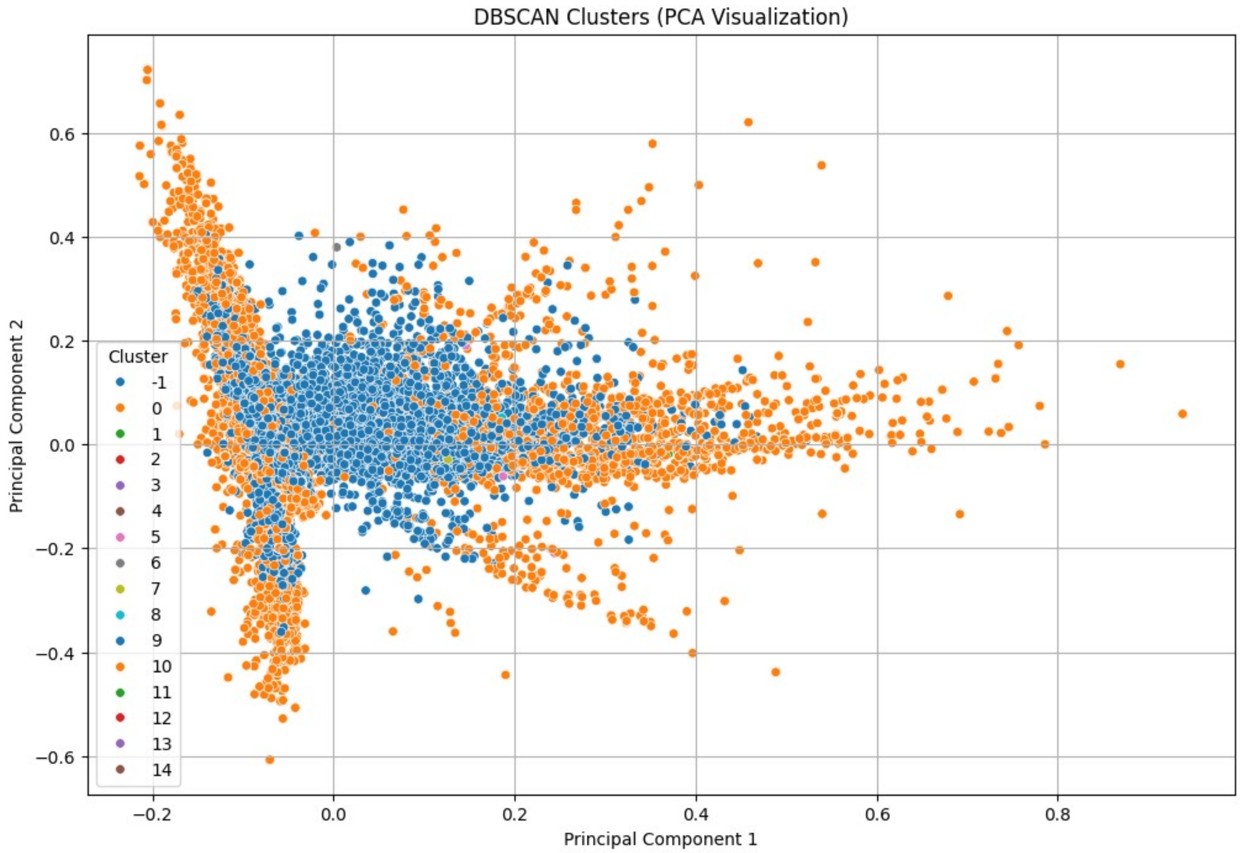
```
array([-1,  0, 11,  1,  4,  8, 10, 12,  6,  9,  2,  5,  3, 14, 13,
7])
```

```python
import matplotlib.pyplot as plt
from sklearn.decomposition import PCA
import seaborn as sns

# Reduce dimensions to 2D with PCA
pca = PCA(n_components=2, random_state=42)
X_pca = pca.fit_transform(X_sampled_tfidf.toarray())

# Add PCA components to the dataframe
sampled_df['PCA_1'] = X_pca[:, 0]
sampled_df['PCA_2'] = X_pca[:, 1]

# Plot
plt.figure(figsize=(12, 8))
sns.scatterplot(
    x='PCA_1', y='PCA_2',
    hue='DBSCAN_Cluster',
    palette='tab10',
    data=sampled_df,
    legend='full',
    s=30
)
plt.title('DBSCAN Clusters (PCA Visualization)')
plt.xlabel('Principal Component 1')
plt.ylabel('Principal Component 2')
plt.legend(title='Cluster')
plt.grid(True)
plt.show()
```



In one paragraph, please compare the results of K-means, DBSCAN, Hierarchical clustering, Word2Vec, and BERT.

The result of the cluster analysis on Amazon mobile reviews showed that each approach had its own benefits. K-Means, being a centroid-based method, had ideal features for widely scattered data because it resulted in well-separated and balanced clusters, even if it was still sensitive to noise and less than effective in dealing with non-spherical shapes. DBSCAN, which is known for coping with outliers and identifying clusters of different shapes, erroneously classified most overlapping cases as negative examples. However, this method makes demands on computation when working on larger datasets; hierarchical clustering produced informative dendrograms that showed clustered relationships between more than one review. Context-aware techniques like Word2Vec enhanced thematic coherence through the semantics-by-representing-word-in-a-vector-context and averaging across reviews-really gave an edge compared to classical TF-IDF ways. Because of their deep sense of context, the BERT embeddings produced the highest precision and semantic alignment of clusters while differentiating sentiment from content.In conclusion, Word2Vec and BERT provided deeper semantic coherence for finer clustering, while K-Means and DBSCAN offered scalable and interpretable approaches with numerical features.

Mandatory Question

Important: Reflective Feedback on this exercise

Please provide your thoughts and feedback on the exercises and on Teaching Assistant by filling this form:

https://docs.google.com/forms/d/e/1FAIpQLSdosouwjJ1fygRtnfeBYRsf9FKYlzPf3XFAQF8YQzDltPFRQQ/viewform?usp=dialog

(Your submission will not be graded if this question is left unanswered)