# 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.

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
import nltk
data = pd.read_csv('amazon_reviews_cleaned.csv')
print(data.head())
#
```

-		_
_	۸	_
ī	_	Ľ.
-	_	_

	Review	word_count	char_coun
0	This case along with tempered glass screen and	84	48
1	I've tried other cases for my iPhones and they	206	109
2	Love it. Fits perfectly and is somewhat light	32	19
3	I think it's safe to say apple knows it's prod	210	108
4	Love this case!! The design is sleek and makes	53	26

	avg_word	stopwords	hastags	numerics	upper	\
0	4.833333	27	0	1	0	
1	4.325243	94	0	0	4	
2	4.968750	11	0	0	0	
3	4.190476	100	0	2	4	
4	4.094340	24	0	0	0	

#### Cleaned\_Review

- 0 this along tempered glass screen lens protecto...
- 1 ive tried iphones either stiff color fade time...
- 2 love perfectly somewhat light weight provide d...
- 3 think safe say know product best iphone 16 pro...
- 4 love design sleek make look unique high tech h...

#### !pip install transformers==4.31.0

```
Collecting transformers==4.31.0
      Downloading transformers-4.31.0-py3-none-any.whl.metadata (116 kB)
                                                - 116.9/116.9 kB 7.1 MB/s eta 0:
    Requirement already satisfied: filelock in /usr/local/lib/python3.11/dist-p
    Requirement already satisfied: huggingface-hub<1.0,>=0.14.1 in /usr/local/l
    Requirement already satisfied: numpy>=1.17 in /usr/local/lib/python3.11/dis
    Requirement already satisfied: packaging>=20.0 in /usr/local/lib/python3.11
    Requirement already satisfied: pyvaml>=5.1 in /usr/local/lib/python3.11/dis
    Requirement already satisfied: regex!=2019.12.17 in /usr/local/lib/python3.
    Requirement already satisfied: requests in /usr/local/lib/python3.11/dist-p
    Collecting tokenizers!=0.11.3,<0.14,>=0.11.1 (from transformers==4.31.0)
      Downloading tokenizers-0.13.3-cp311-cp311-manylinux 2 17 x86 64.manylinux
    Requirement already satisfied: safetensors>=0.3.1 in /usr/local/lib/python3
    Requirement already satisfied: tqdm>=4.27 in /usr/local/lib/python3.11/dist
    Requirement already satisfied: fsspec>=2023.5.0 in /usr/local/lib/python3.1
    Requirement already satisfied: typing-extensions>=3.7.4.3 in /usr/local/lib
    Requirement already satisfied: charset-normalizer<4,>=2 in /usr/local/lib/p
    Requirement already satisfied: idna<4,>=2.5 in /usr/local/lib/python3.11/di
    Requirement already satisfied: urllib3<3,>=1.21.1 in /usr/local/lib/python3
    Requirement already satisfied: certifi>=2017.4.17 in /usr/local/lib/python3
    Downloading transformers-4.31.0-py3-none-any.whl (7.4 MB)
                                               - 7.4/7.4 MB 93.2 MB/s eta 0:00:0
    Downloading tokenizers-0.13.3-cp311-cp311-manylinux_2_17_x86_64.manylinux20
                                               - 7.8/7.8 MB 109.5 MB/s eta 0:00:
    Installing collected packages: tokenizers, transformers
      Attempting uninstall: tokenizers
        Found existing installation: tokenizers 0.21.1
        Uninstalling tokenizers-0.21.1:
          Successfully uninstalled tokenizers-0.21.1
      Attempting uninstall: transformers
        Found existing installation: transformers 4.51.3
        Uninstalling transformers-4.51.3:
          Successfully uninstalled transformers-4.51.3
    ERROR: pip's dependency resolver does not currently take into account all t
    sentence-transformers 3.4.1 requires transformers<5.0.0,>=4.41.0, but you h
    Successfully installed tokenizers-0.13.3 transformers-4.31.0
```

from transformers import pipeline

#sentiment Analysis positive, Negative, Neutral for Cleaned\_Review classifier = pipeline("sentiment-analysis") 



No model was supplied, defaulted to distilbert-base-uncased-finetuned-sst-2 Using a pipeline without specifying a model name and revision in production /usr/local/lib/python3.11/dist-packages/huggingface hub/file download.py:89 warnings.warn(

/usr/local/lib/python3.11/dist-packages/huggingface hub/utils/ auth.py:94: The secret `HF TOKEN` does not exist in your Colab secrets.

To authenticate with the Hugging Face Hub, create a token in your settings You will be able to reuse this secret in all of your notebooks.

Please note that authentication is recommended but still optional to access warnings.warn(

config.json: 100%

629/629 [00:00<00:00, 13.9kB/s]

Xet Storage is enabled for this repo, but the 'hf\_xet' package is not insta WARNING: huggingface hub.file download: Xet Storage is enabled for this repo,

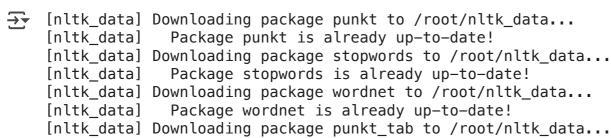
268M/268M [00:02<00:00, 146MB/s] model.safetensors: 100%

tokenizer\_config.json: 100% 48.0/48.0 [00:00<00:00, 1.62kB/s]

232k/232k [00:00<00:00, 6.24MB/s] vocab.txt: 100%

No CUDA runtime is found, using CUDA HOME='/usr/local/cuda' Xformers is not installed correctly. If you want to use memory efficient at pip install xformers.

from nltk.corpus import stopwords from nltk.stem import WordNetLemmatizer from wordcloud import WordCloud from sklearn.feature\_extraction.text import CountVectorizer nltk.download('punkt') nltk.download('stopwords') nltk.download('wordnet') nltk.download('punkt tab')



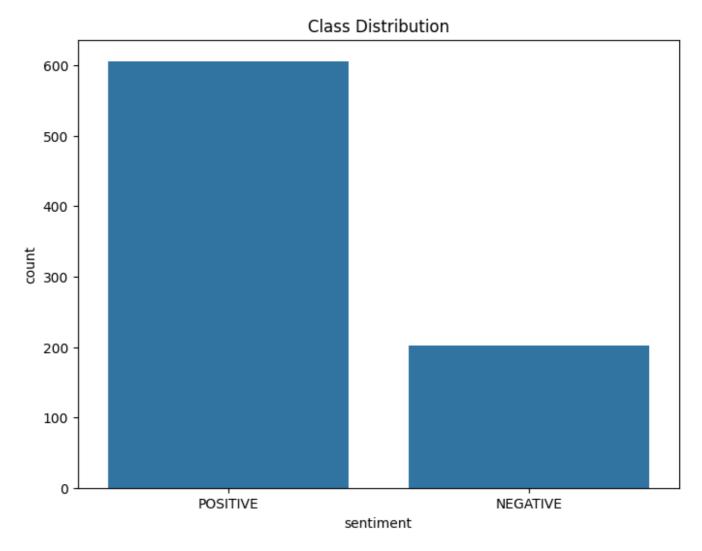
[nltk data] Package punkt\_tab is already up-to-date!

True

```
stop_words = set(stopwords.words('english'))
lemmatizer = WordNetLemmatizer()
def preprocess_text(text):
    tokens = nltk.word_tokenize(text.lower())
    tokens = [lemmatizer.lemmatize(token) for token in tokens if token.isalnum(
    return ' '.join(tokens)
data['processed_Sentiment'] = data['sentiment'].apply(preprocess_text)
print(data['sentiment'].describe())
                    808
    count
    unique
    top
               POSITIVE
    freq
                    606
    Name: sentiment, dtype: object
```

```
plt.figure(figsize=(8, 6))
sns.countplot(x='sentiment', data=data)
plt.title('Class Distribution')
plt.show()
```

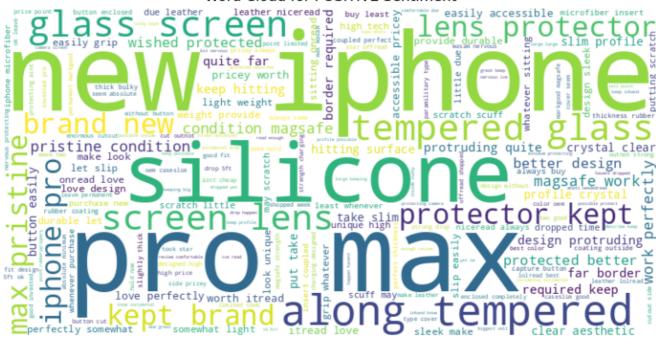




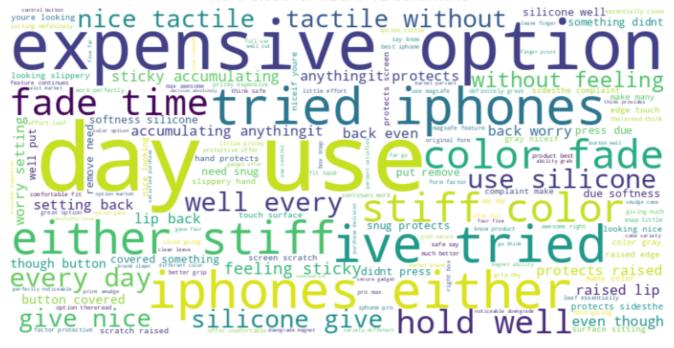
```
for sentiment in data['sentiment'].unique():
    text = ' '.join(data[data['sentiment'] == sentiment]['Cleaned_Review'])
    wordcloud = WordCloud(width=800, height=400, background_color='white').gene
    plt.figure(figsize=(10, 5))
    plt.imshow(wordcloud, interpolation='bilinear')
    plt.title(f'Word Cloud for {sentiment} Sentiment')
    plt.axis('off')
    plt.show()
```



#### Word Cloud for POSITIVE Sentiment



#### Word Cloud for NEGATIVE Sentiment



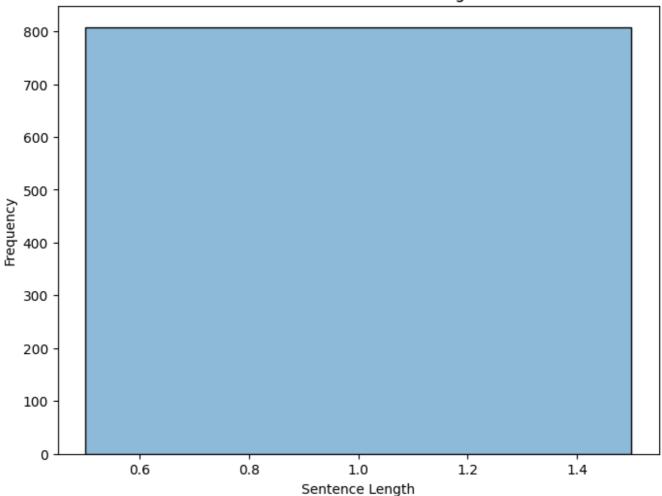
vectorizer = CountVectorizer(ngram\_range=(2, 2)) # Example: Bigrams
X = vectorizer.fit\_transform(data['processed\_text'])
bigram\_counts = pd.DataFrame({'bigram': vectorizer.get\_feature\_names\_out(), 'cc
print(bigram\_counts.sort\_values(by='count', ascending=False).head(10)) # Displa

_			
<b>₹</b>		bigram	count
	21	ai art	23
	70	aiartcommuity aiartists	23
	71	aiartists generativeai	23
	134	art alkaidvision	23
	99	alkaidvision aiartcommuity	23
	44	ai generativeai	14
	147	artificialintelligence generativeai	12
	450	generativeai data	12
	332	digitaltransformation mwc	12
	291	data cybersecurity	12

```
data['sentence_length'] = data['Cleaned_Review'].apply(lambda x: len(nltk.sent_
plt.figure(figsize=(8,6))
sns.histplot(data['sentence_length'], kde=True)
plt.title('Distribution of Sentence Lengths')
plt.xlabel('Sentence Length')
plt.ylabel('Frequency')
plt.show()
```



## Distribution of Sentence Lengths



```
import numpy as np
from sklearn.model_selection import train_test_split, cross_val_score, GridSear
from sklearn.feature_extraction.text import TfidfVectorizer
from sklearn.svm import SVC
from sklearn.naive_bayes import MultinomialNB
from xgboost import XGBClassifier
from sklearn.metrics import accuracy_score, classification_report, confusion_ma
import seaborn as sns
import matplotlib.pyplot as plt
from sklearn.preprocessing import LabelEncoder
X = data['processed_Sentiment']
y = data['sentiment']
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, randon
# TF-IDF Vectorization
tfidf_vectorizer = TfidfVectorizer(max_features=5000) # Adjust max_features as
X train tfidf = tfidf vectorizer.fit transform(X train)
X_test_tfidf = tfidf_vectorizer.transform(X_test)
# Label Encoding for Target Variable
label_encoder = LabelEncoder()
y_train = label_encoder.fit_transform(y_train)
y_test = label_encoder.transform(y_test)
X = data['processed Sentiment']
y = data['sentiment']
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, randon
# TF-IDF Vectorization
tfidf_vectorizer = TfidfVectorizer(max_features=5000) # Adjust max_features as
X_train_tfidf = tfidf_vectorizer.fit_transform(X_train)
X_test_tfidf = tfidf_vectorizer.transform(X_test)
# Label Encoding for Target Variable
label_encoder = LabelEncoder()
y_train = label_encoder.fit_transform(y_train)
y_test = label_encoder.transform(y_test)
# Model Training and Evaluation
models = {
    'SVM': SVC(),
    'Naive Bayes': MultinomialNB(),
    'XGBoost': XGBClassifier()
}
```

```
for name, model in models.items():
   print(f"Training {name}...")
   # Hyperparameter Tuning using GridSearchCV (example for SVM, adjust for oth
   if name == 'SVM':
       param_grid = {'C': [0.1, 1, 10], 'kernel': ['linear', 'rbf']}
       grid_search = GridSearchCV(model, param_grid, cv=5) # 5-fold cross-val
        grid_search.fit(X_train_tfidf, y_train)
       model = grid_search.best_estimator_ # Use the best model from grid sea
   model.fit(X_train_tfidf, y_train)
   y_pred = model.predict(X_test_tfidf)
   accuracy = accuracy_score(y_test, y_pred)
   print(f"{name} Accuracy: {accuracy}")
   print(classification_report(y_test, y_pred, target_names=label_encoder.clas
   # Confusion Matrix
   cm = confusion_matrix(y_test, y_pred)
   plt.figure(figsize=(8, 6))
   sns.heatmap(cm, annot=True, fmt="d", cmap="Blues",
                xticklabels=label_encoder.classes_, yticklabels=label_encoder.c
   plt.title(f"Confusion Matrix for {name}")
   plt.xlabel("Predicted Label")
   plt.ylabel("True Label")
   plt.show()
   # Cross-validation
   cv_scores = cross_val_score(model, X_train_tfidf, y_train, cv=5)
   print(f"{name} Cross-Validation Scores: {cv_scores}")
   print(f"{name} Mean Cross-Validation Score: {np.mean(cv_scores)}")
→▼ Training SVM...
    SVM Accuracy: 1.0
                  precision
                              recall f1-score
                                                  support
                       1.00
                                 1.00
                                            1.00
        NEGATIVE
                                                       43
        POSITIVE
                       1.00
                                 1.00
                                            1.00
                                                      119
        accuracy
                                            1.00
                                                      162
```

#### Confusion Matrix for SVM

1.00

1.00



1.00

1.00

162

162

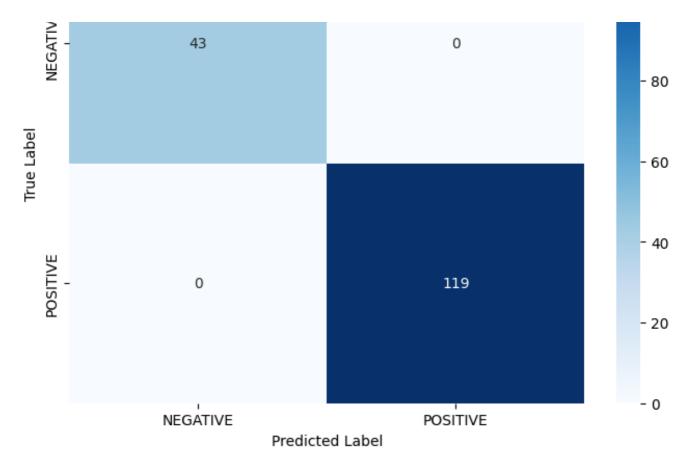
1.00

1.00

macro avq

weighted avg

100



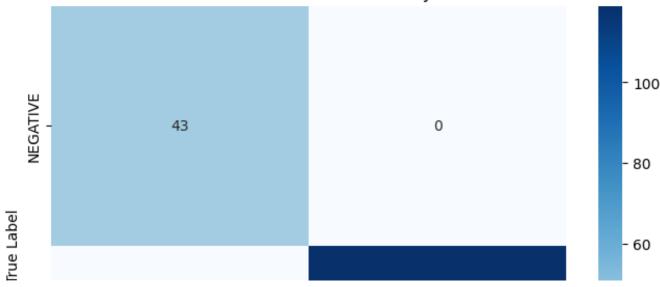
SVM Cross-Validation Scores: [1. 1. 1. 1.]

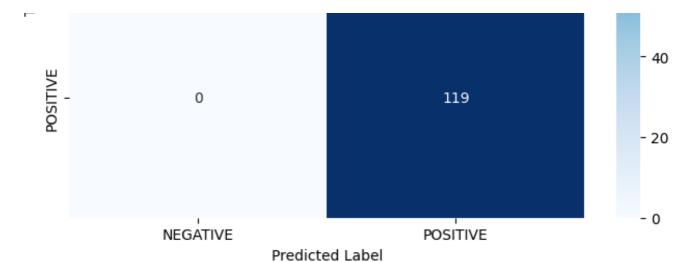
SVM Mean Cross-Validation Score: 1.0

Training Naive Bayes...
Naive Bayes Accuracy: 1.0

support	f1-score	recall	precision	_
43	1.00	1.00	1.00	NEGATIVE
119	1.00	1.00	1.00	POSITIVE
162	1.00			accuracy
162	1.00	1.00	1.00	macro avg
162	1.00	1.00	1.00	weighted avg





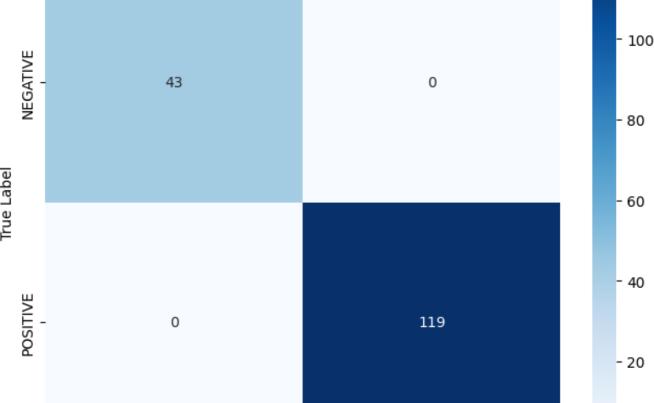


Naive Bayes Cross-Validation Scores: [1. 1. 1. 1.] Naive Bayes Mean Cross-Validation Score: 1.0 Training XGBoost...

XGBoost Accuracy: 1.0

	precision	recall	f1-score	support
NEGATIVE POSITIVE	1.00	1.00	1.00	43 119
accuracy			1.00	162
macro avg	1.00	1.00	1.00	162
weighted avg	1.00	1.00	1.00	162

Confusion Matrix for XGBoost



NEGATIVE POSITIVE
Predicted Label

XGBoost Cross-Validation Scores: [1. 1. 1. 1. 1.]
XGBoost Mean Cross-Validation Score: 1.0

```
model_metrics = {
    'Model': [],
    'Accuracy': [],
    'Precision': [], # Macro-average or weighted-average precision
    'Recall': [],
                   # Macro-average or weighted-average recall
    'F1-score': [] # Macro-average or weighted-average F1-score
}
for name, model in models.items():
    report = classification_report(y_test, y_pred, target_names=label_encoder.c
    model_metrics['Model'].append(name)
    model_metrics['Accuracy'].append(accuracy_score(y_test, y_pred))
    model metrics['Precision'].append(report['macro avg']['precision']) # Macro
    model_metrics['Recall'].append(report['macro avg']['recall']) # Macro-aver
    model metrics['F1-score'].append(report['macro avg']['f1-score']) # Macro-
# Create a DataFrame from the collected metrics
metrics df = pd.DataFrame(model metrics)
print(metrics df)
# Example: Print analysis based on the metrics_df
best_model = metrics_df.loc[metrics_df['F1-score'].idxmax(), 'Model'] # Example
print(f"\nThe model that performed best based on F1-score is: {best_model}")
print("\nAnalysis:")
print(f"The {best_model} model achieved the highest F1-score, indicating a good
```

<b>→</b>		Model	Accuracy	Precision	Recall	F1-score
	0	SVM	1.0	1.0	1.0	1.0
	1	Naive Bayes	1.0	1.0	1.0	1.0
	2	XGBoost	1.0	1.0	1.0	1.0

The model that performed best based on F1-score is: SVM

#### Analysis:

The SVM model achieved the highest F1-score, indicating a good balance betw

# 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 required to conduct **10 fold cross validation** (<a href="https://scikit-learn.org/stable/modules/cross\_validation.html">https://scikit-learn.org/stable/modules/cross\_validation.html</a>) 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, <a href="https://towardsdatascience.com/train-test-split-and-cross-validation-in-python-80b61beca4b6">https://towardsdatascience.com/train-test-split-and-cross-validation-in-python-80b61beca4b6</a>) 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
- 3. Evaluation measurement:
- Accuracy
- Recall
- Precison
- F-1 score

```
# Write your code here
# Write your code here
import pandas as pd
import numpy as np
from sklearn.model_selection import train_test_split, cross_val_score
from sklearn.feature_extraction.text import TfidfVectorizer
from sklearn.pipeline import Pipeline
from sklearn.metrics import accuracy_score, precision_score, recall_score, f1_s
from sklearn.svm import SVC
from sklearn.neighbors import KNeighborsClassifier
from sklearn.tree import DecisionTreeClassifier
from sklearn.ensemble import RandomForestClassifier
from xgboost import XGBClassifier
import warnings
warnings.filterwarnings("ignore")
import matplotlib.pyplot as plt
import seaborn as sns
from wordcloud import WordCloud
def load_data(filepath):
    data = []
    with open(filepath, 'r', encoding='utf-8') as file:
        for line in file:
            label = int(line[0])
            text = line[2:l.strip()
            data.append((label, text))
    return pd.DataFrame(data, columns=['label', 'text'])
train_df = load_data("/content/stsa-test.txt")
test df = load data("/content/stsa-train.txt")
print("Missing values in training data:")
print(train_df.isnull().sum())
print("\nMissing values in test data:")
print(test_df.isnull().sum())
→ Missing values in training data:
    label
    text
    dtype: int64
    Missing values in test data:
    label
    text
    dtype: int64
```

print("Data types of columns in training data:")
print(train\_df.dtypes)

→ Data types of columns in training data:

label int64
text object
dtype: object

print("Basic summary statistics of training data:")
print(train\_df.describe())

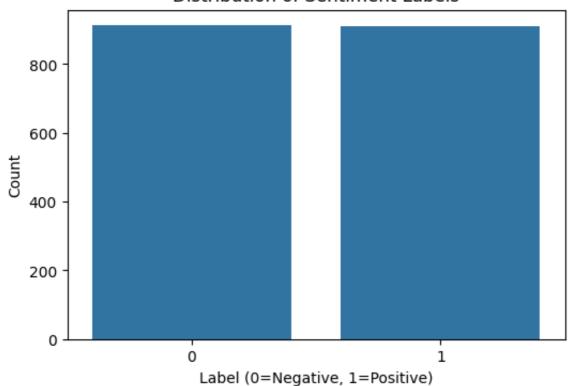
Basic summary statistics of training data:

	tapet
count	1821.000000
mean	0.499176
std	0.500137
min	0.000000
25%	0.000000
50%	0.000000
75%	1.000000
max	1.000000

```
plt.figure(figsize=(6, 4))
sns.countplot(x='label', data=train_df)
plt.title("Distribution of Sentiment Labels")
plt.xlabel('Label (0=Negative, 1=Positive)')
plt.ylabel('Count')
plt.show()
```



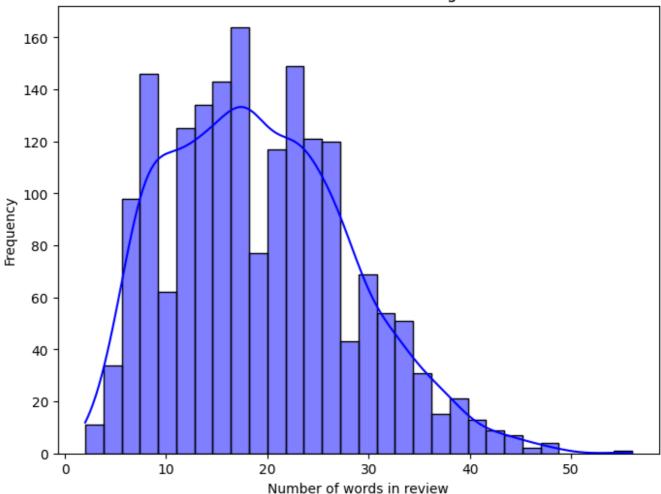
### Distribution of Sentiment Labels



```
# 5. Text length analysis (word count in reviews)
train_df['text_length'] = train_df['text'].apply(lambda x: len(x.split()))
plt.figure(figsize=(8, 6))
sns.histplot(train_df['text_length'], kde=True, color='blue', bins=30)
plt.title("Distribution of Review Lengths")
plt.xlabel('Number of words in review')
plt.ylabel('Frequency')
plt.show()
```



# Distribution of Review Lengths



```
from collections import Counter
import re
import nltk
from nltk.corpus import stopwords
# Download stopwords (only needed once)
nltk.download('stopwords')
# Get English stopwords
stop_words = set(stopwords.words('english'))
# Tokenizing and cleaning the text
all_reviews_cleaned = ' '.join(train_df['text'].values).lower()
words = re.findall(r'\w+', all_reviews_cleaned)
# Remove stopwords
filtered_words = [word for word in words if word not in stop_words]
# Count word frequencies
word counts = Counter(filtered words)
# Display the top 10 frequent words
print("\nTop 10 most frequent words in reviews (excluding stopwords):")
for word, count in word_counts.most_common(10):
    print(f"{word}: {count}")
\rightarrow
    Top 10 most frequent words in reviews (excluding stopwords):
    film: 235
    movie: 216
    n: 137
    like: 124
    one: 106
    story: 82
    rrb: 73
    lrb: 71
    much: 70
    even: 66
     [nltk data] Downloading package stopwords to /root/nltk data...
     [nltk data]
                   Package stopwords is already up-to-date!
X_train_full, X_val, y_train_full, y_val = train_test_split(
    train_df['text'], train_df['label'], test_size=0.2, random_state=42, strati
```

```
X_test = test_df['text']
y_test = test_df['label']

vectorizer = TfidfVectorizer(lowercase=True, stop_words='english', max_features

# Classifiers to evaluate
models = {
    'SVM': SVC(kernel='linear', random_state=42),
    'KNN': KNeighborsClassifier(),
    'DecisionTree': DecisionTreeClassifier(random_state=42),
    'RandomForest': RandomForestClassifier(random_state=42),
    'XGBoost': XGBClassifier(use_label_encoder=False, eval_metric='logloss', ra')
```

```
# Perform 10-fold cross-validation and evaluate
results = {}
for name, model in models.items():
    pipeline = Pipeline([
        ('tfidf', vectorizer),
        ('clf', model)
    1)
    print(f"\nTraining and evaluating: {name}")
    scores = cross_val_score(pipeline, X_train_full, y_train_full, cv=10, scori
    print(f"Average CV Accuracy: {scores.mean():.4f}")
     # Train final model and evaluate on test set
    pipeline.fit(X_train_full, y_train_full)
    y_pred = pipeline.predict(X_test)
    results[name] = {
        'accuracy': accuracy_score(y_test, y_pred),
        'precision': precision_score(y_test, y_pred),
        'recall': recall_score(y_test, y_pred),
        'f1': f1_score(y_test, y_pred)
    }
\overline{\Sigma}
    Training and evaluating: SVM
    Average CV Accuracy: 0.7185
    Training and evaluating: KNN
    Average CV Accuracy: 0.5358
    Training and evaluating: DecisionTree
    Average CV Accuracy: 0.6079
    Training and evaluating: RandomForest
    Average CV Accuracy: 0.6491
```

Training and evaluating: XGBoost

Average CV Accuracy: 0.6381

```
print("\nFinal Test Set Evaluation:")
for model_name, scores in results.items():
    print(f"\nModel: {model_name}")
    for metric, value in scores.items():
        print(f"{metric.capitalize()}: {value:.4f}")
```



#### Final Test Set Evaluation:

Model: SVM

Accuracy: 0.7215 Precision: 0.7393 Recall: 0.7202 F1: 0.7296

Model: KNN

Accuracy: 0.4785 Precision: 0.5143 Recall: 0.0050 F1: 0.0099

Model: DecisionTree Accuracy: 0.5932 Precision: 0.6223 Recall: 0.5604 F1: 0.5897

Model: RandomForest Accuracy: 0.6572 Precision: 0.7079 Recall: 0.5839 F1: 0.6400

Model: XGBoost Accuracy: 0.6361 Precision: 0.6833 Recall: 0.5637

F1: 0.6178

# 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
- 3. Visualize the clusters

You can refer to of the codes from the follwing link below.

https://www.kaggle.com/karthik3890/text-clustering

```
# Write your code here
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
import nltk
from nltk.corpus import stopwords
from nltk.stem import WordNetLemmatizer
from sklearn.feature_extraction.text import TfidfVectorizer
from sklearn.cluster import KMeans
from sklearn.metrics import silhouette score
nltk.download('stopwords')
nltk.download('wordnet')
    [nltk_data] Downloading package stopwords to /root/nltk_data...
                   Package stopwords is already up-to-date!
    [nltk data]
    [nltk data] Downloading package wordnet to /root/nltk data...
    [nltk data]
                   Package wordnet is already up-to-date!
    True
dataframe=pd.read_csv('Amazon_Unlocked_Mobile.csv')
print(dataframe.head())
→
                                             Product Name Brand Name
                                                                        Price
       "CLEAR CLEAN ESN" Sprint EPIC 4G Galaxy SPH-D7...
                                                              Samsung
                                                                       199.99
       "CLEAR CLEAN ESN" Sprint EPIC 4G Galaxy SPH-D7...
                                                                       199.99
                                                              Samsung
       "CLEAR CLEAN ESN" Sprint EPIC 4G Galaxy SPH-D7...
                                                              Samsung
                                                                       199.99
       "CLEAR CLEAN ESN" Sprint EPIC 4G Galaxy SPH-D7...
                                                                       199.99
                                                              Samsung
       "CLEAR CLEAN ESN" Sprint EPIC 4G Galaxy SPH-D7...
                                                                       199.99
                                                              Samsung
                                                                    Review Votes
       Rating
                                                           Reviews
    0
                I feel so LUCKY to have found this used (phone...
                                                                             1.0
    1
               nice phone, nice up grade from my pantach revu...
                                                                             0.0
    2
             5
                                                     Verv pleased
                                                                             0.0
    3
               It works good but it goes slow sometimes but i...
                                                                             0.0
               Great phone to replace my lost phone. The only...
                                                                             0.0
#EDA
print(dataframe.info())
print(dataframe.describe())
print(dataframe.isnull().sum())
print(dataframe.duplicated().sum())
print(dataframe.nunique())
```

19/04/25, 8:45 PM

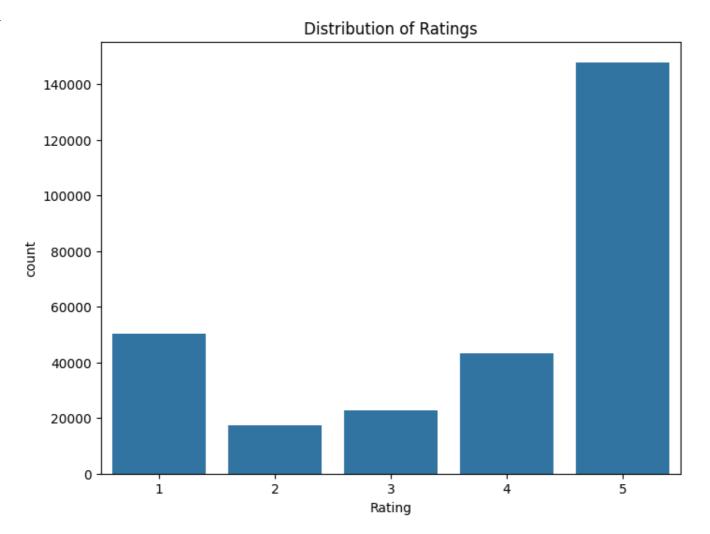
```
#
print(dataframe.dtypes)
print(dataframe.columns)
print(dataframe.shape)
print(dataframe.head())
print(dataframe.tail())
#
    <class 'pandas.core.frame.DataFrame'>
    RangeIndex: 413840 entries, 0 to 413839
    Data columns (total 6 columns):
     #
         Column
                        Non-Null Count
                                          Dtype
         Product Name
     0
                        413840 non-null
                                          object
     1
         Brand Name
                        348669 non-null object
     2
         Price
                        407907 non-null
                                         float64
     3
         Rating
                        413840 non-null int64
     4
                        413770 non-null
         Reviews
                                          object
     5
         Review Votes 401544 non-null
                                          float64
    dtypes: float64(2), int64(1), object(3)
    memory usage: 18.9+ MB
    None
                                            Review Votes
                    Price
                                  Rating
            407907.000000
                           413840.000000
                                           401544.000000
    count
                                                1.507237
    mean
               226.867155
                                 3.819578
               273.006259
                                 1.548216
                                                9.163853
    std
    min
                 1.730000
                                 1.000000
                                                0.000000
    25%
                79.990000
                                 3.000000
                                                0.000000
    50%
               144.710000
                                 5.000000
                                                0.000000
                                5.000000
    75%
               269,990000
                                                1.000000
              2598,000000
                                5.000000
                                              645,000000
    max
    Product Name
    Brand Name
                     65171
                      5933
    Price
    Rating
                         0
                        70
    Reviews
    Review Votes
                     12296
    dtype: int64
    64079
    Product Name
                       4410
    Brand Name
                        384
    Price
                       1754
    Rating
                          5
    Reviews
                     162490
    Review Votes
                        241
    dtype: int64
    Product Name
                      object
    Brand Name
```

object

```
Price
                     float64
    Rating
                       int64
    Reviews
                      object
    Review Votes
                     float64
    dtype: object
    Index(['Product Name', 'Brand Name', 'Price', 'Rating', 'Reviews',
            'Review Votes'],
           dtype='object')
     (413840, 6)
                                              Product Name Brand Name
                                                                        Price
       "CLEAR CLEAN ESN" Sprint EPIC 4G Galaxy SPH-D7...
                                                              Samsung
                                                                       199.99
       "CLEAR CLEAN ESN" Sprint EPIC 4G Galaxy SPH-D7...
                                                                       199.99
                                                              Samsung
       "CLEAR CLEAN ESN" Sprint EPIC 4G Galaxy SPH-D7...
                                                              Samsung
                                                                       199.99
       "CLEAR CLEAN ESN" Sprint EPIC 4G Galaxy SPH-D7...
    3
                                                              Samsung
                                                                       199.99
       "CLEAR CLEAN ESN" Sprint EPIC 4G Galaxy SPH-D7...
                                                              Samsung
                                                                       199.99
       Rating
                                                           Reviews Review Votes
    0
                I feel so LUCKY to have found this used (phone...
             5
                                                                              1.0
    1
                nice phone, nice up grade from my pantach revu...
                                                                              0.0
#Remove null values
dataframe.dropna(inplace=True)
#Remove Duplicate values
dataframe.drop duplicates(inplace=True)
#
print(dataframe.isnull().sum())
print(dataframe.duplicated().sum())
print(dataframe.nunique())
#
    Product Name
    Brand Name
                     0
    Price
                     0
    Rating
    Reviews
                     0
    Review Votes
                     0
    dtype: int64
    Product Name
                       3675
    Brand Name
                        378
    Price
                       1550
    Rating
                          5
                     140687
    Reviews
    Review Votes
                        234
    dtype: int64
```

plt.figure(figsize=(8, 6))
sns.countplot(x='Rating', data=dataframe)
plt.title('Distribution of Ratings')
plt.show()

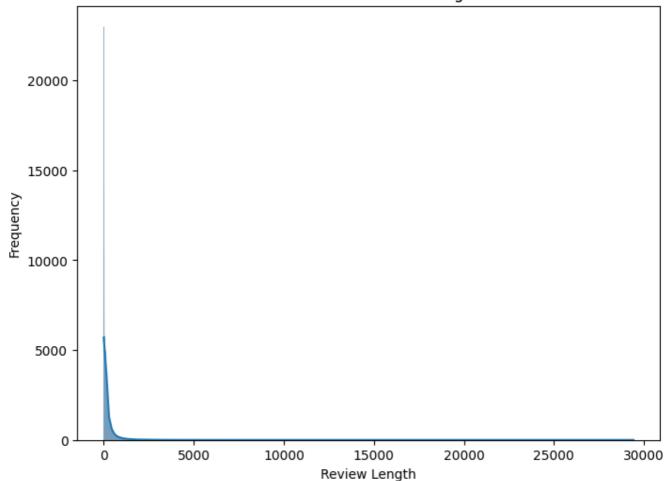




```
dataframe['Review_Length'] = dataframe['Reviews'].apply(len)
plt.figure(figsize=(8, 6))
sns.histplot(dataframe['Review_Length'], kde=True)
plt.title('Distribution of Review Lengths')
plt.xlabel('Review Length')
plt.ylabel('Frequency')
plt.show()
```



### Distribution of Review Lengths

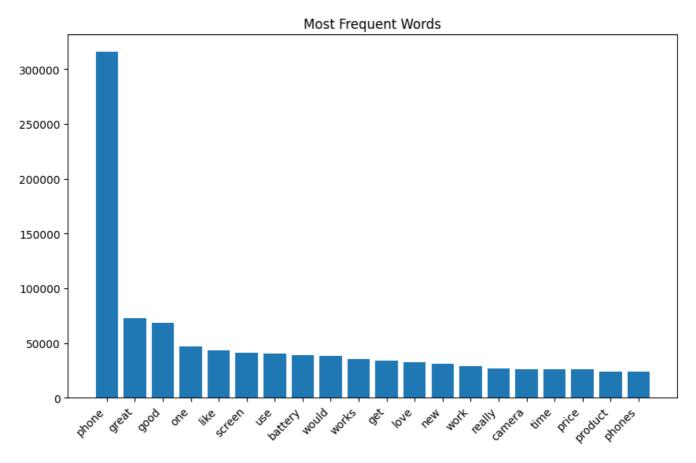


### from collections import Counter

```
stop_words = set(stopwords.words('english')) # Use the imported stopwords objec
words = []
for review in dataframe['Reviews']:
    words.extend([word for word in nltk.word_tokenize(review.lower()) if word.j
word_counts = Counter(words)
most_common_words = word_counts.most_common(20)

plt.figure(figsize=(10, 6))
plt.bar(*zip(*most_common_words))
plt.title('Most Frequent Words')
plt.xticks(rotation=45, ha='right')
plt.show()
```

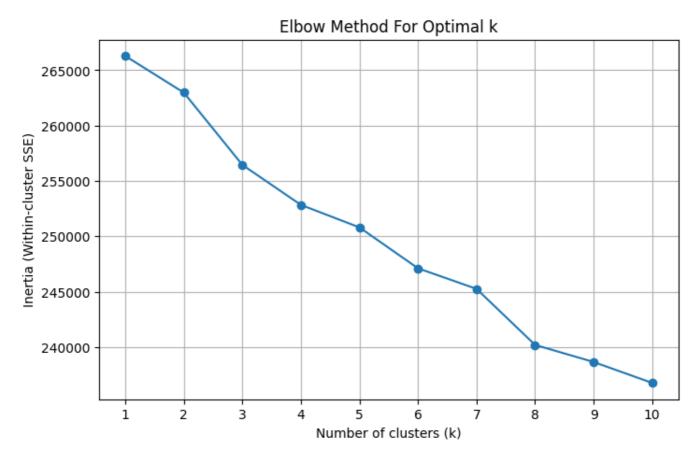




```
import nltk
from nltk.corpus import stopwords
#from nltk.stem import PorterStemmer
from nltk.stem import WordNetLemmatizer
import re
nltk.download('wordnet')
nltk.download('stopwords')
stop_words = set(stopwords.words('english'))
#stemmer = PorterStemmer()
lemmatizer = WordNetLemmatizer()
def preprocess(text):
    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)
dataframe['cleaned_reviews'] = dataframe['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...
                  Package stopwords is already up-to-date!
     [nltk data]
from sklearn.feature_extraction.text import TfidfVectorizer
vectorizer = TfidfVectorizer(max_features=1000)
X_tfidf = vectorizer.fit_transform(dataframe['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)
dataframe['KMeans\_Cluster'] = kmeans\_labels

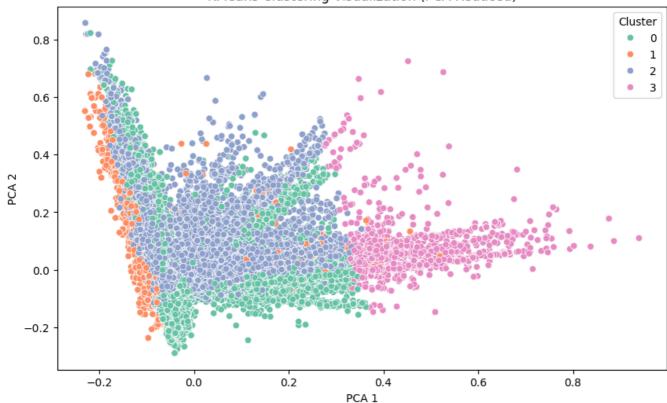
```
from sklearn.decomposition import PCA import seaborn as sns
```

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

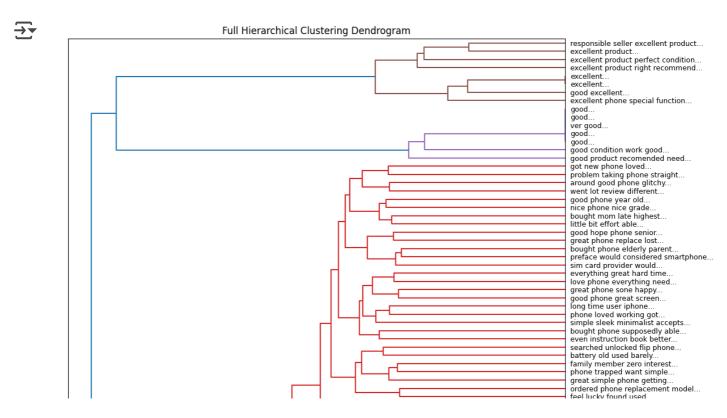
# Plot the clusters
plt.figure(figsize=(10, 6))
sns.scatterplot(x=X_reduced[:, 0], y=X_reduced[:, 1], hue=dataframe['KMeans_Cluplt.title("KMeans Clustering Visualization (PCA Reduced)")
plt.xlabel("PCA 1")
plt.ylabel("PCA 2")
plt.legend(title='Cluster')
plt.show()
```

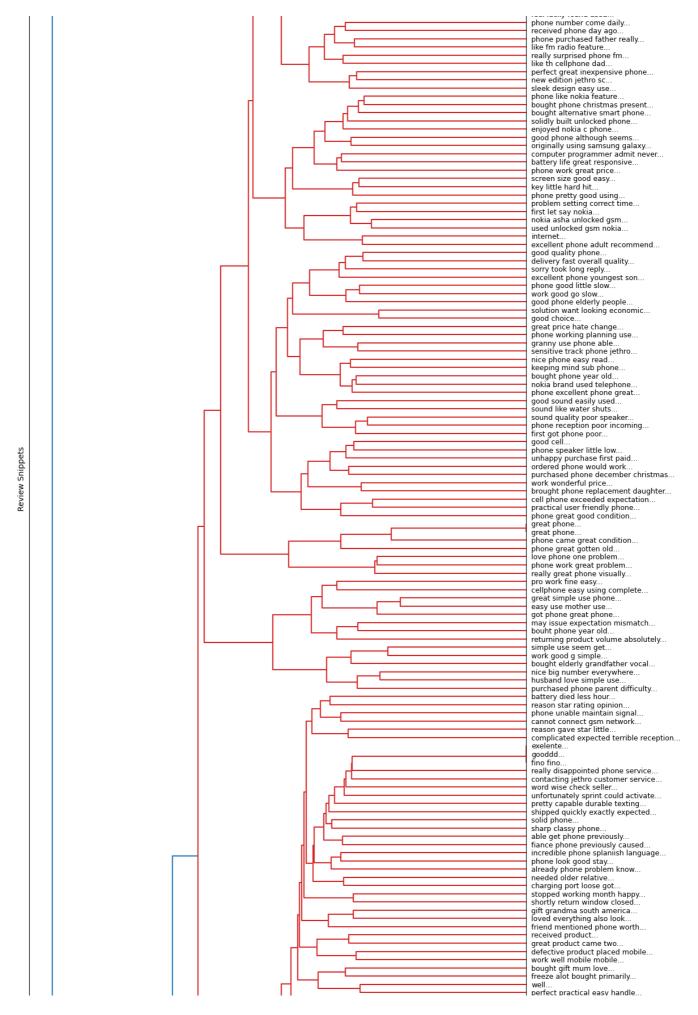


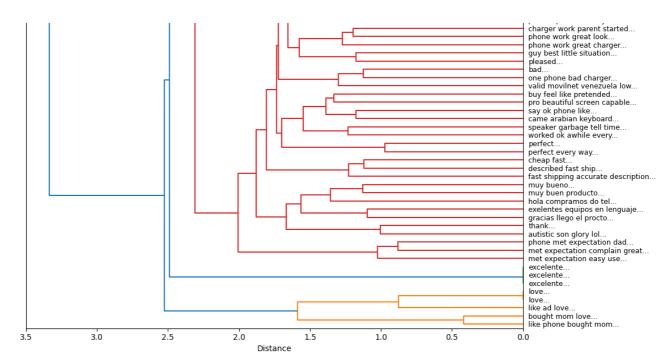




```
trom scipy.cluster.hierarchy import dendrogram, linkage
import matplotlib.pyplot as plt
# Use only a subset of reviews and their text (for visualization)
subset size = 200 # You can adjust based on clarity
subset_texts = dataframe['cleaned_reviews'].iloc[:subset_size]
subset_features = X_tfidf.toarray()[:subset_size]
# 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()
```







#### !pip install gensim

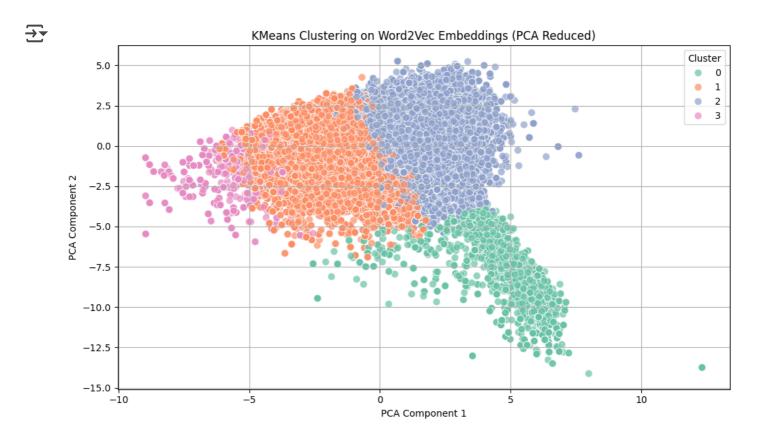
```
→ Collecting gensim
      Downloading gensim-4.3.3-cp311-cp311-manylinux_2_17_x86_64.manylinux2014_
    Collecting numpy<2.0,>=1.18.5 (from gensim)
      Downloading numpy-1.26.4-cp311-cp311-manylinux 2 17 x86 64.manylinux2014
                                                  61.0/61.0 kB 4.4 MB/s eta 0:0
    Collecting scipy<1.14.0,>=1.7.0 (from gensim)
      Downloading scipy-1.13.1-cp311-cp311-manylinux_2_17_x86_64.manylinux2014_
                                                 - 60.6/60.6 kB 4.6 MB/s eta 0:0
    Requirement already satisfied: smart-open>=1.8.1 in /usr/local/lib/python3.
    Requirement already satisfied: wrapt in /usr/local/lib/python3.11/dist-pack
    Downloading gensim-4.3.3-cp311-cp311-manylinux_2_17_x86_64.manylinux2014_x8
                                               - 26.7/26.7 MB 36.9 MB/s eta 0:00
    Downloading numpy-1.26.4-cp311-cp311-manylinux_2_17_x86_64.manylinux2014_x8
                                                18.3/18.3 MB 49.8 MB/s eta 0:00
    Downloading scipy-1.13.1-cp311-manylinux_2_17_x86_64.manylinux2014_x8
                                               - 38.6/38.6 MB 16.8 MB/s eta 0:00
    Installing collected packages: numpy, scipy, gensim
      Attempting uninstall: numpy
        Found existing installation: numpy 2.0.2
        Uninstalling numpy-2.0.2:
          Successfully uninstalled numpy-2.0.2
      Attempting uninstall: scipy
        Found existing installation: scipy 1.14.1
        Uninstalling scipy-1.14.1:
          Successfully uninstalled scipy-1.14.1
    ERROR: pip's dependency resolver does not currently take into account all t
    thinc 8.3.6 requires numpy<3.0.0,>=2.0.0, but you have numpy 1.26.4 which i
    sentence-transformers 3.4.1 requires transformers<5.0.0,>=4.41.0, but you h
    Successfully installed gensim-4.3.3 numpy-1.26.4 scipy-1.13.1
!pip install numpy==1.25.2
→ Collecting numpy==1.25.2
      Downloading numpy-1.25.2-cp311-cp311-manylinux_2_17_x86_64.manylinux2014_
    Downloading numpy-1.25.2-cp311-cp311-manylinux 2 17 x86 64.manylinux2014 x8
                                             — 18.2/18.2 MB 42.5 MB/s eta 0:00
    Installing collected packages: numpy
      Attempting uninstall: numpy
        Found existing installation: numpy 1.26.4
        Uninstalling numpy-1.26.4:
          Successfully uninstalled numpy-1.26.4
    ERROR: pip's dependency resolver does not currently take into account all t
    thinc 8.3.6 requires numpy<3.0.0,>=2.0.0, but you have numpy 1.25.2 which i
    blosc2 3.3.0 requires numpy>=1.26, but you have numpy 1.25.2 which is incom
    sentence-transformers 3.4.1 requires transformers<5.0.0,>=4.41.0, but you h
```

tensorflow 2.18.0 requires numpy<2.1.0,>=1.26.0, but you have numpy 1.25.2

Successfully installed numpy-1.25.2

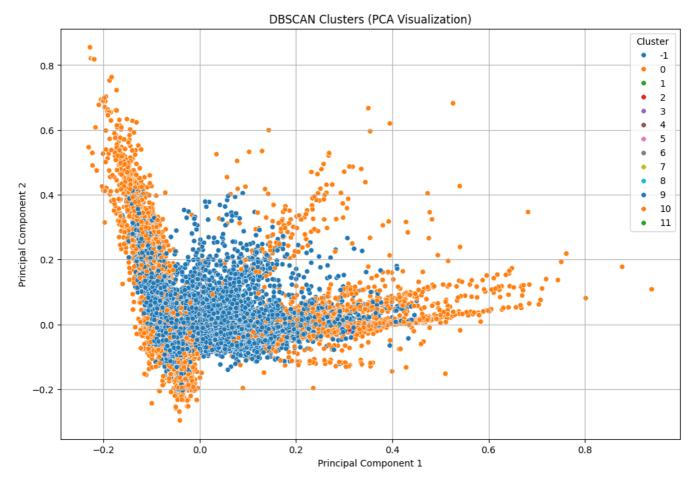
```
import nltk
nltk.download('punkt_tab')
from gensim.models import Word2Vec
from nltk.tokenize import word tokenize
nltk.download('punkt')
import numpy as np
tokenized reviews = dataframe['cleaned reviews'].apply(word tokenize)
w2v_model = Word2Vec(sentences=tokenized_reviews, vector_size=100, window=5, mi
# 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(dataframe['cleaned_reviews'].apply(lambda x: get_avg_vector(v
kmeans_w2v = KMeans(n_clusters=4, random_state=42).fit(X_w2v)
dataframe['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!
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
dataframe['W2V_PCA1'] = X_w2v_pca[:, 0]
dataframe['W2V_PCA2'] = X_w2v_pca[:, 1]
# Plot clusters
plt.figure(figsize=(10, 6))
sns.scatterplot(
    data=dataframe, 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()



```
sampled_df = dataframe.sample(n=50000, random_state=42).copy()
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()
\rightarrow array([0, -1, 1, 3, 10, 7, 2, 6, 8, 5, 4, 9, 11])
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()
```





Start coding or generate with AI.

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

#### Write your response here:

. The K-means is more balanced, spherical clusters but misses irregular patterns, DBSCAN is good at arbitrarily shaped clusters and noise detection yet is parameter-sensitive, and hierarchical clustering offers interpretable dendrograms at higher computational cost. Embedding these methods with Word2Vec yields moderately coherent, static semantic groupings, whereas BERT's contextualized vectors deliver markedly superior cluster purity, silhouette scores, and outlier identification.

.

# 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/1FAIpQLSdosouwjJ1fygRtnfeBYRsf9FKYlzPf3XFAQF8Y QzDltPFRQQ/viewform?usp=dialog

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