News Article Classification

NLP Project

Part B : News Article Classification

Deliverables

1. Data Collection and Preprocessing

[58]:
```
import pandas as pd
import re
import nltk
from nltk.corpus import stopwords
from nltk.tokenize import word_tokenize
from nltk.stem import WordNetLemmatizer

# Download NLTK resources if not already downloaded
nltk.download('stopwords')
nltk.download('punkt')
nltk.download('wordnet')

# Load the dataset (update the file path if necessary)
df = pd.read_csv("data_news.csv")

# Display basic information about the dataset
print("Dataset Information:")
print(df.info())
print("\nFirst few rows:")
print(df.head())
```

```
[nltk_data] Downloading package stopwords to
[nltk_data]     C:\Users\91951\AppData\Roaming\nltk_data…
[nltk_data]   Package stopwords is already up-to-date!
[nltk_data] Downloading package punkt to
[nltk_data]     C:\Users\91951\AppData\Roaming\nltk_data…
[nltk_data]   Package punkt is already up-to-date!
[nltk_data] Downloading package wordnet to
[nltk_data]     C:\Users\91951\AppData\Roaming\nltk_data…
[nltk_data]   Package wordnet is already up-to-date!
```

```
Dataset Information:
<class 'pandas.core.frame.DataFrame'>
```

```
RangeIndex: 50000 entries, 0 to 49999
Data columns (total 5 columns):
 #   Column             Non-Null Count  Dtype
---  ------             --------------  -----
 0   category           50000 non-null  object
 1   headline           50000 non-null  object
 2   links              50000 non-null  object
 3   short_description  50000 non-null  object
 4   keywords           47332 non-null  object
dtypes: object(5)
memory usage: 1.9+ MB
None

First few rows:
   category                                           headline  \
0  WELLNESS              143 Miles in 35 Days: Lessons Learned
1  WELLNESS       Talking to Yourself: Crazy or Crazy Helpful?
2  WELLNESS  Crenezumab: Trial Will Gauge Whether Alzheimer…
3  WELLNESS                     Oh, What a Difference She Made
4  WELLNESS                                   Green Superfoods

                                               links  \
0  https://www.huffingtonpost.com/entry/running-l…
1  https://www.huffingtonpost.com/entry/talking-t…
2  https://www.huffingtonpost.com/entry/crenezuma…
3  https://www.huffingtonpost.com/entry/meaningfu…
4  https://www.huffingtonpost.com/entry/green-sup…

                                   short_description  \
0  Resting is part of training. I've confirmed wh…
1  Think of talking to yourself as a tool to coac…
2  The clock is ticking for the United States to …
3  If you want to be busy, keep trying to be perf…
4  First, the bad news: Soda bread, corned beef a…

                             keywords
0                     running-lessons
1           talking-to-yourself-crazy
2  crenezumab-alzheimers-disease-drug
3                     meaningful-life
4                     green-superfoods
```

[60]:

```python
# The 'links' column is not useful for text classification, so we remove it
df = df.drop(columns=["links"])

# Fill missing values in the 'keywords' column with an empty string
df["keywords"].fillna("", inplace=True)
```

```python
# Initialize Lemmatizer
lemmatizer = WordNetLemmatizer()
stop_words = set(stopwords.words("english"))

# Function to clean and preprocess text
def preprocess_text(text):
    text = text.lower()  # Convert to lowercase
    text = re.sub(r"[^\w\s]", "", text)  # Remove punctuation
    text = re.sub(r"\d+", "", text)  # Remove numbers
    words = word_tokenize(text)  # Tokenization
    words = [word for word in words if word not in stop_words]  # Remove␣
 ↪stopwords
    words = [lemmatizer.lemmatize(word) for word in words]  # Lemmatization
    return " ".join(words)  # Convert list back to string

# Apply the function to text columns
text_columns = ["headline", "short_description", "keywords"]
for col in text_columns:
    df[col] = df[col].apply(preprocess_text)
```

[62]:

```python
# Check the dataset structure
print(df.info())

# Display some preprocessed text
print(df.head())
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 50000 entries, 0 to 49999
Data columns (total 4 columns):
 #   Column             Non-Null Count  Dtype
---  ------             --------------  -----
 0   category           50000 non-null  object
 1   headline           50000 non-null  object
 2   short_description  50000 non-null  object
 3   keywords           50000 non-null  object
dtypes: object(4)
memory usage: 1.5+ MB
None
   category                                           headline  \
0  WELLNESS                            mile day lesson learned
1  WELLNESS                        talking crazy crazy helpful
2  WELLNESS  crenezumab trial gauge whether alzheimers drug…
3  WELLNESS                                 oh difference made
4  WELLNESS                                   green superfoods

                                   short_description  \
0  resting part training ive confirmed sort alrea…
```

```
1  think talking tool coach challenge narrate exp…
2  clock ticking united state find cure team work…
3  want busy keep trying perfect want happy focus…
4  first bad news soda bread corned beef beer hig…

                          keywords
0                   runninglessons
1          talkingtoyourselfcrazy
2  crenezumabalzheimersdiseasedrug
3                   meaningfullife
4                  greensuperfoods
```

2. Feature Extraction

[65]:
```python
from sklearn.feature_extraction.text import TfidfVectorizer

# Combine headline, short description, and keywords
df["combined_text"] = df["headline"] + " " + df["short_description"] + " " +␣
↪df["keywords"].fillna("")

# Initialize TF-IDF Vectorizer
tfidf_vectorizer = TfidfVectorizer(max_features=5000)

# Fit and transform the combined text data
X_tfidf = tfidf_vectorizer.fit_transform(df["combined_text"])

# Convert to a DataFrame for better understanding
tfidf_df = pd.DataFrame(X_tfidf.toarray(), columns=tfidf_vectorizer.
↪get_feature_names_out())

# Display shape and first few rows
print("TF-IDF Feature Shape:", tfidf_df.shape)
print(tfidf_df.head())
```

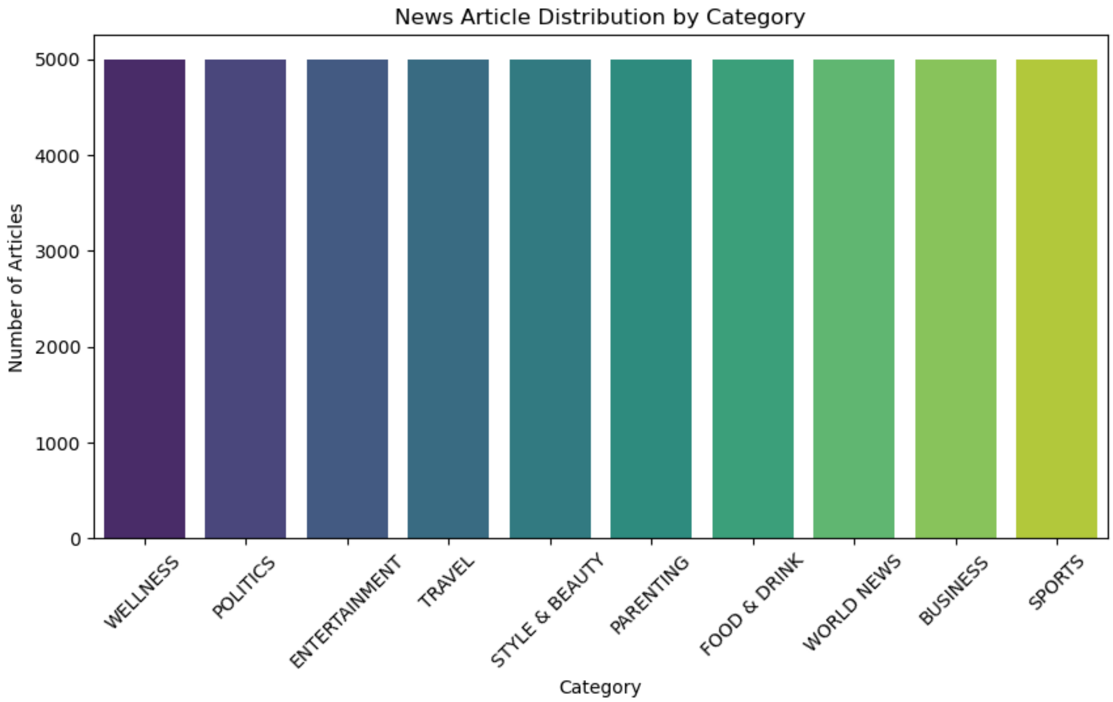
```
TF-IDF Feature Shape: (50000, 5000)
   aaron  abandoned  abc  ability  able  aboard  abortion  abroad  absence  \
0    0.0        0.0  0.0      0.0   0.0     0.0       0.0     0.0      0.0
1    0.0        0.0  0.0      0.0   0.0     0.0       0.0     0.0      0.0
2    0.0        0.0  0.0      0.0   0.0     0.0       0.0     0.0      0.0
3    0.0        0.0  0.0      0.0   0.0     0.0       0.0     0.0      0.0
4    0.0        0.0  0.0      0.0   0.0     0.0       0.0     0.0      0.0

   absolute  …  youre  youth  youtube  youve  zealand  zen  zero  zika  zoe  \
0       0.0  …    0.0    0.0      0.0    0.0      0.0  0.0   0.0   0.0  0.0
1       0.0  …    0.0    0.0      0.0    0.0      0.0  0.0   0.0   0.0  0.0
2       0.0  …    0.0    0.0      0.0    0.0      0.0  0.0   0.0   0.0  0.0
3       0.0  …    0.0    0.0      0.0    0.0      0.0  0.0   0.0   0.0  0.0
4       0.0  …    0.0    0.0      0.0    0.0      0.0  0.0   0.0   0.0  0.0
```

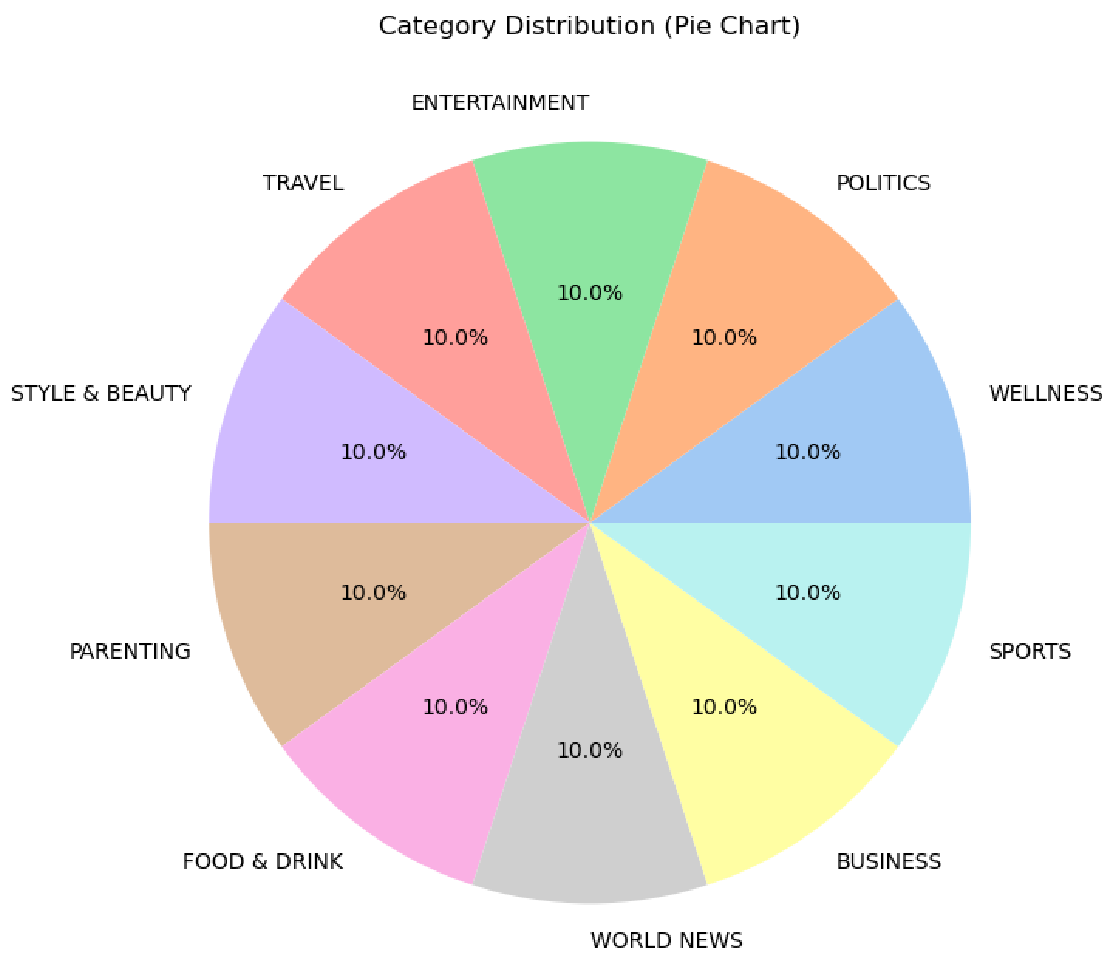
```
   zone
0   0.0
1   0.0
2   0.0
3   0.0
4   0.0

[5 rows x 5000 columns]
```

[67]:
```python
import matplotlib.pyplot as plt
import seaborn as sns

# Count articles per category
category_counts = df["category"].value_counts()

# Display category distribution
print(category_counts)
```

```
category
WELLNESS          5000
POLITICS          5000
ENTERTAINMENT     5000
TRAVEL            5000
STYLE & BEAUTY    5000
PARENTING         5000
FOOD & DRINK      5000
WORLD NEWS        5000
BUSINESS          5000
SPORTS            5000
Name: count, dtype: int64
```

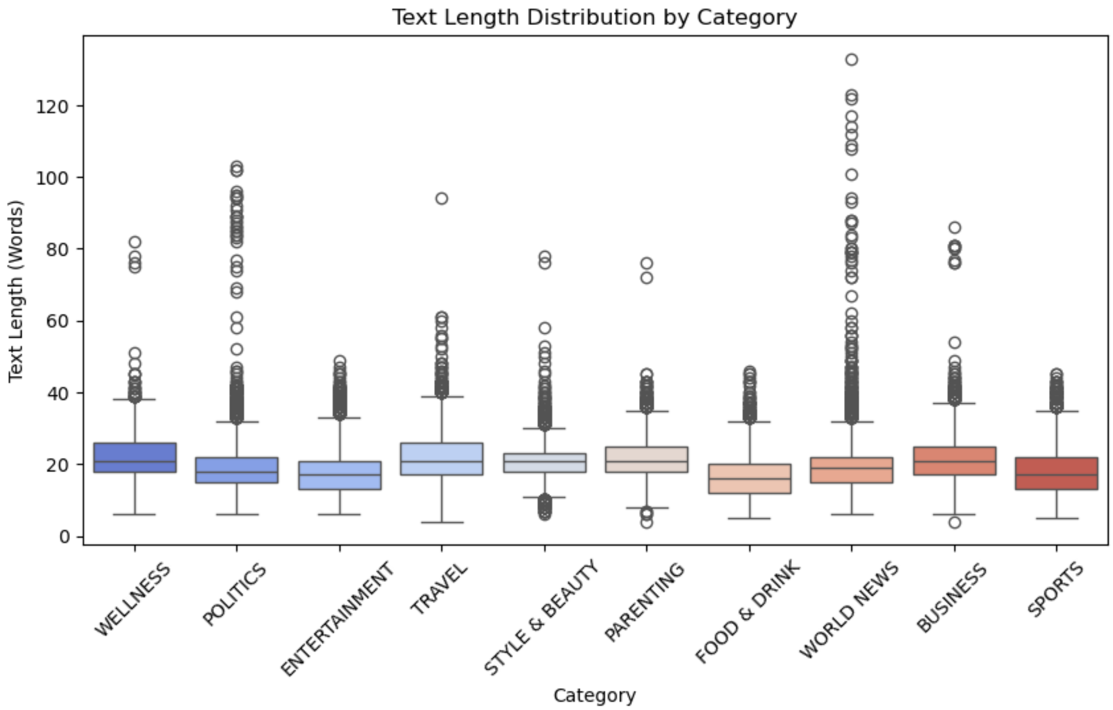
[69]:
```python
# Bar Plot
plt.figure(figsize=(10, 5))
sns.barplot(x=category_counts.index, y=category_counts.values,␣
 ↪palette="viridis")
plt.xticks(rotation=45)
plt.xlabel("Category")
plt.ylabel("Number of Articles")
plt.title("News Article Distribution by Category")
plt.show()

# Pie Chart
plt.figure(figsize=(8, 8))
plt.pie(category_counts, labels=category_counts.index, autopct="%1.1f%%",␣
 ↪colors=sns.color_palette("pastel"))
plt.title("Category Distribution (Pie Chart)")
plt.show()
```


News Article Distribution by Category
Number of Articles
5000
4000
3000
2000
1000
0
WELLNESS
POLITICS
ENTERTAINMENT
TRAVEL
STYLE & BEAUTY
PARENTING
FOOD & DRINK
WORLD NEWS
BUSINESS
SPORTS
Category



[71]:

```
# Create a new column for text length
df["text_length"] = df["combined_text"].apply(lambda x: len(x.split()))

# Boxplot to compare text lengths per category
plt.figure(figsize=(10, 5))
sns.boxplot(x="category", y="text_length", data=df, palette="coolwarm")
plt.xticks(rotation=45)
plt.xlabel("Category")
plt.ylabel("Text Length (Words)")
plt.title("Text Length Distribution by Category")
plt.show()
```



3. Model Development and Training

[74]:
```
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import LabelEncoder

# Encode category labels into numbers
label_encoder = LabelEncoder()
df["category_encoded"] = label_encoder.fit_transform(df["category"])

# Split into train & test sets (80% train, 20% test)
X_train, X_test, y_train, y_test = train_test_split(X_tfidf,␣
↪df["category_encoded"], test_size=0.2, random_state=42)

print("Train Size:", X_train.shape, "Test Size:", X_test.shape)
```

```
Train Size: (40000, 5000) Test Size: (10000, 5000)
```

[76]:
```
from sklearn.linear_model import LogisticRegression
from sklearn.naive_bayes import MultinomialNB
from sklearn.svm import SVC

# Initialize models
log_reg = LogisticRegression(max_iter=1000)
nb = MultinomialNB()
svm = SVC(kernel="linear")
```

```python
# Train models
log_reg.fit(X_train, y_train)
nb.fit(X_train, y_train)
svm.fit(X_train, y_train)

# Predictions
y_pred_log = log_reg.predict(X_test)
y_pred_nb = nb.predict(X_test)
y_pred_svm = svm.predict(X_test)
```

[77]:

```python
# Tune Logistic Regression
from sklearn.model_selection import GridSearchCV

# Define parameter grid
param_grid_log = {"C": [0.1, 1, 10, 100]}

# Perform GridSearchCV
grid_log = GridSearchCV(LogisticRegression(max_iter=1000), param_grid_log,␣
 ↪cv=5, scoring="accuracy", n_jobs=-1)
grid_log.fit(X_train, y_train)

# Best parameters
print("Best Parameters (Logistic Regression):", grid_log.best_params_)

# Train optimized model
best_log = grid_log.best_estimator_
```

```
Best Parameters (Logistic Regression): {'C': 1}
```

[80]:

```python
# Tune Naive Bayes
# Define parameter grid
param_grid_nb = {"alpha": [0.1, 0.5, 1, 5, 10]}

# Perform GridSearchCV
grid_nb = GridSearchCV(MultinomialNB(), param_grid_nb, cv=5,␣
 ↪scoring="accuracy", n_jobs=-1)
grid_nb.fit(X_train, y_train)

# Best parameters
print("Best Parameters (Naive Bayes):", grid_nb.best_params_)

# Train optimized model
best_nb = grid_nb.best_estimator_
```

```
Best Parameters (Naive Bayes): {'alpha': 1}
```

[82]:
```python
# Tune SVM
# Define parameter grid
param_grid_svm = {"C": [0.1, 1, 10], "kernel": ["linear", "rbf"]}

# Perform GridSearchCV
grid_svm = GridSearchCV(SVC(), param_grid_svm, cv=5, scoring="accuracy",␣
 ↪n_jobs=-1)
grid_svm.fit(X_train, y_train)

# Best parameters
print("Best Parameters (SVM):", grid_svm.best_params_)

# Train optimized model
best_svm = grid_svm.best_estimator_
```

```
Best Parameters (SVM): {'C': 10, 'kernel': 'rbf'}
```

[83]:
```python
from sklearn.model_selection import cross_val_score

# Define the number of folds
cv_folds = 5

# Logistic Regression Cross-Validation
log_cv_scores = cross_val_score(best_log, X_train, y_train, cv=cv_folds,␣
 ↪scoring="accuracy")
print("Logistic Regression Cross-Validation Accuracy:", log_cv_scores.mean())

# Naive Bayes Cross-Validation
nb_cv_scores = cross_val_score(best_nb, X_train, y_train, cv=cv_folds,␣
 ↪scoring="accuracy")
print("Naive Bayes Cross-Validation Accuracy:", nb_cv_scores.mean())

# SVM Cross-Validation
svm_cv_scores = cross_val_score(best_svm, X_train, y_train, cv=cv_folds,␣
 ↪scoring="accuracy")
print("SVM Cross-Validation Accuracy:", svm_cv_scores.mean())
```

```
Logistic Regression Cross-Validation Accuracy: 0.79245
Naive Bayes Cross-Validation Accuracy: 0.7802
SVM Cross-Validation Accuracy: 0.810225
```

4. Model Evaluation

[85]:
```python
from sklearn.metrics import accuracy_score, classification_report,␣
 ↪confusion_matrix

# Function to evaluate and print model performance
def evaluate_model(model, X_test, y_test, model_name):
```

```python
    y_pred = model.predict(X_test)

    print(f"\n Model: {model_name}")
    print("Accuracy:", accuracy_score(y_test, y_pred))
    print("Classification Report:\n", classification_report(y_test, y_pred))
    print("Confusion Matrix:\n", confusion_matrix(y_test, y_pred))

# Evaluate Logistic Regression
evaluate_model(best_log, X_test, y_test, "Logistic Regression")

# Evaluate Naive Bayes
evaluate_model(best_nb, X_test, y_test, "Naive Bayes")

# Evaluate SVM
evaluate_model(best_svm, X_test, y_test, "SVM")
```

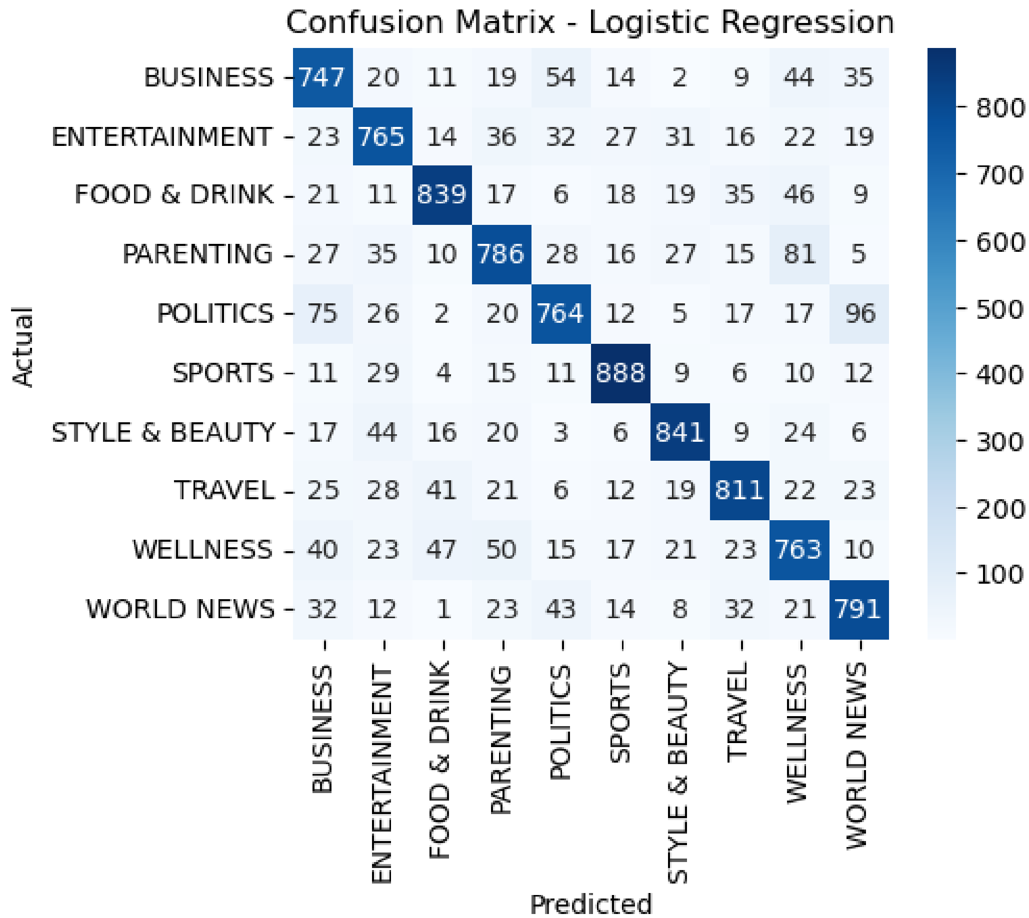
```
 Model: Logistic Regression
Accuracy: 0.7995
Classification Report:
               precision    recall  f1-score   support

           0       0.73      0.78      0.76       955
           1       0.77      0.78      0.77       985
           2       0.85      0.82      0.84      1021
           3       0.78      0.76      0.77      1030
           4       0.79      0.74      0.77      1034
           5       0.87      0.89      0.88       995
           6       0.86      0.85      0.85       986
           7       0.83      0.80      0.82      1008
           8       0.73      0.76      0.74      1009
           9       0.79      0.81      0.80       977

    accuracy                           0.80     10000
   macro avg       0.80      0.80      0.80     10000
weighted avg       0.80      0.80      0.80     10000

Confusion Matrix:
 [[747  20  11  19  54  14   2   9  44  35]
 [ 23 765  14  36  32  27  31  16  22  19]
 [ 21  11 839  17   6  18  19  35  46   9]
 [ 27  35  10 786  28  16  27  15  81   5]
 [ 75  26   2  20 764  12   5  17  17  96]
 [ 11  29   4  15  11 888   9   6  10  12]
 [ 17  44  16  20   3   6 841   9  24   6]
 [ 25  28  41  21   6  12  19 811  22  23]
 [ 40  23  47  50  15  17  21  23 763  10]
 [ 32  12   1  23  43  14   8  32  21 791]]
```

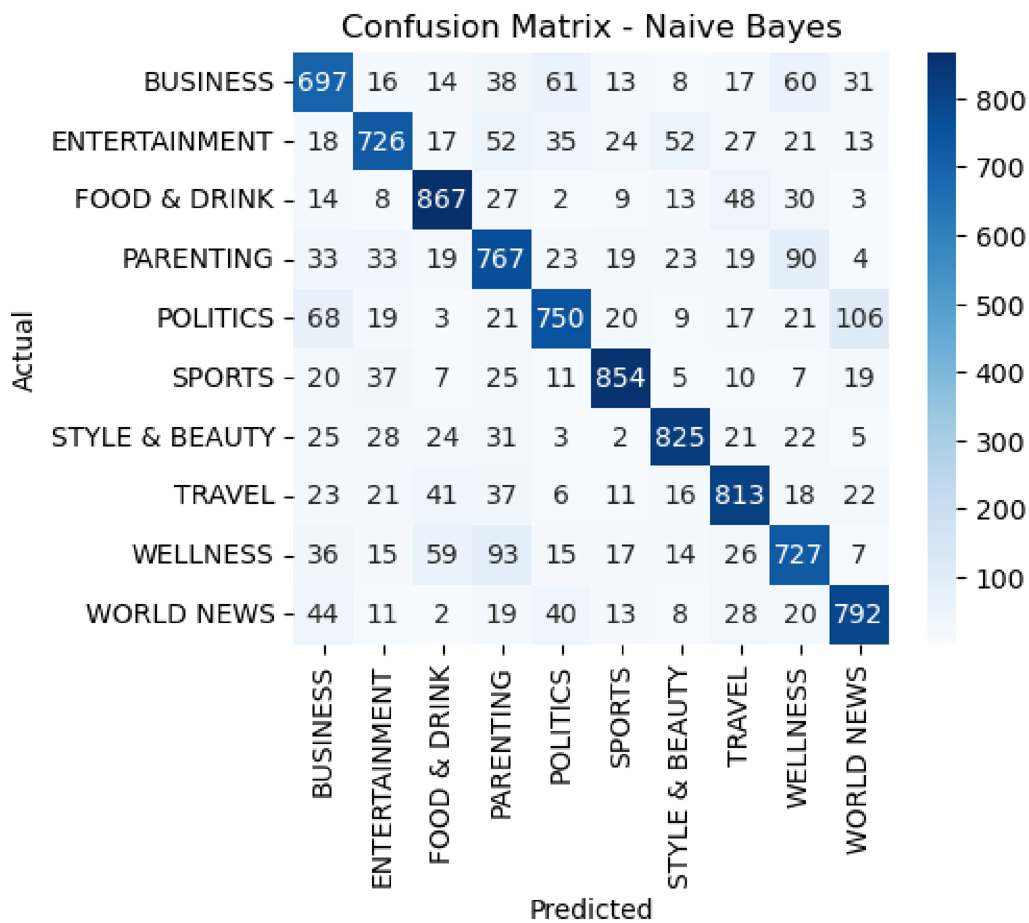
```
 Model: Naive Bayes
Accuracy: 0.7818
Classification Report:
              precision    recall  f1-score   support

           0       0.71      0.73      0.72       955
           1       0.79      0.74      0.76       985
           2       0.82      0.85      0.84      1021
           3       0.69      0.74      0.72      1030
           4       0.79      0.73      0.76      1034
           5       0.87      0.86      0.86       995
           6       0.85      0.84      0.84       986
           7       0.79      0.81      0.80      1008
           8       0.72      0.72      0.72      1009
           9       0.79      0.81      0.80       977

    accuracy                           0.78     10000
   macro avg       0.78      0.78      0.78     10000
weighted avg       0.78      0.78      0.78     10000

Confusion Matrix:
 [[697  16  14  38  61  13   8  17  60  31]
 [ 18 726  17  52  35  24  52  27  21  13]
 [ 14   8 867  27   2   9  13  48  30   3]
 [ 33  33  19 767  23  19  23  19  90   4]
 [ 68  19   3  21 750  20   9  17  21 106]
 [ 20  37   7  25  11 854   5  10   7  19]
 [ 25  28  24  31   3   2 825  21  22   5]
 [ 23  21  41  37   6  11  16 813  18  22]
 [ 36  15  59  93  15  17  14  26 727   7]
 [ 44  11   2  19  40  13   8  28  20 792]]

 Model: SVM
Accuracy: 0.8174
Classification Report:
              precision    recall  f1-score   support

           0       0.80      0.86      0.83       955
           1       0.77      0.80      0.78       985
           2       0.85      0.84      0.85      1021
           3       0.78      0.76      0.77      1030
           4       0.81      0.76      0.78      1034
           5       0.93      0.93      0.93       995
           6       0.87      0.85      0.86       986
           7       0.83      0.81      0.82      1008
           8       0.73      0.77      0.75      1009
           9       0.80      0.81      0.81       977
```

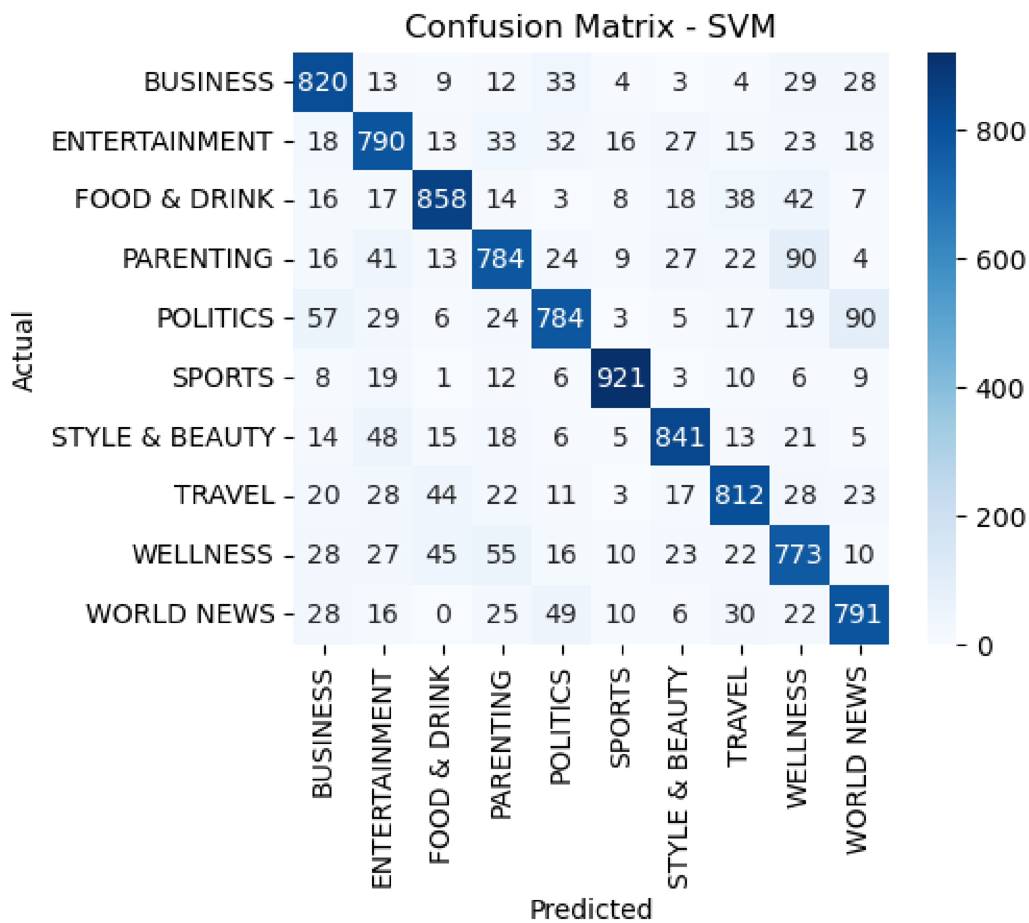
```
    accuracy                           0.82     10000
   macro avg       0.82      0.82      0.82     10000
weighted avg       0.82      0.82      0.82     10000

Confusion Matrix:
 [[820  13   9  12  33   4   3   4  29  28]
 [ 18 790  13  33  32  16  27  15  23  18]
 [ 16  17 858  14   3   8  18  38  42   7]
 [ 16  41  13 784  24   9  27  22  90   4]
 [ 57  29   6  24 784   3   5  17  19  90]
 [  8  19   1  12   6 921   3  10   6   9]
 [ 14  48  15  18   6   5 841  13  21   5]
 [ 20  28  44  22  11   3  17 812  28  23]
 [ 28  27  45  55  16  10  23  22 773  10]
 [ 28  16   0  25  49  10   6  30  22 791]]
```

[86]:

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

# Function to plot confusion matrix
def plot_confusion_matrix(model, X_test, y_test, model_name):
    y_pred = model.predict(X_test)
    cm = confusion_matrix(y_test, y_pred)

    plt.figure(figsize=(5,4))
    sns.heatmap(cm, annot=True, fmt="d", cmap="Blues",␣
 ↪xticklabels=label_encoder.classes_, yticklabels=label_encoder.classes_)
    plt.xlabel("Predicted")
    plt.ylabel("Actual")
    plt.title(f"Confusion Matrix - {model_name}")
    plt.show()

# Plot for Logistic Regression
plot_confusion_matrix(best_log, X_test, y_test, "Logistic Regression")

# Plot for Naive Bayes
plot_confusion_matrix(best_nb, X_test, y_test, "Naive Bayes")

# Plot for SVM
plot_confusion_matrix(best_svm, X_test, y_test, "SVM")
```


Confusion Matrix - Logistic Regression
Actual
Predicted
BUSINESS
ENTERTAINMENT
FOOD & DRINK
PARENTING
POLITICS
SPORTS
STYLE & BEAUTY
TRAVEL
WELLNESS
WORLD NEWS
747 20 11 19 54 14 2 9 44 35
23 765 14 36 32 27 31 16 22 19
21 11 839 17 6 18 19 35 46 9
27 35 10 786 28 16 27 15 81 5
75 26 2 20 764 12 5 17 17 96
11 29 4 15 11 888 9 6 10 12
17 44 16 20 3 6 841 9 24 6
25 28 41 21 6 12 19 811 22 23
40 23 47 50 15 17 21 23 763 10
32 12 1 23 43 14 8 32 21 791
800
700
600
500
400
300
200
100


Confusion Matrix - Naive Bayes
Actual
Predicted
BUSINESS
ENTERTAINMENT
FOOD & DRINK
PARENTING
POLITICS
SPORTS
STYLE & BEAUTY
TRAVEL
WELLNESS
WORLD NEWS
697 16 14 38 61 13 8 17 60 31
18 726 17 52 35 24 52 27 21 13
14 8 867 27 2 9 13 48 30 3
33 33 19 767 23 19 23 19 90 4
68 19 3 21 750 20 9 17 21 106
20 37 7 25 11 854 5 10 7 19
25 28 24 31 3 2 825 21 22 5
23 21 41 37 6 11 16 813 18 22
36 15 59 93 15 17 14 26 727 7
44 11 2 19 40 13 8 28 20 792
800
700
600
500
400
300
200
100



[88]:
```python
# Function to get model evaluation metrics
def get_model_metrics(model, X_test, y_test):
    y_pred = model.predict(X_test)
    accuracy = accuracy_score(y_test, y_pred)
    report = classification_report(y_test, y_pred, output_dict=True)
    f1_score = report["weighted avg"]["f1-score"]
    precision = report["weighted avg"]["precision"]
    recall = report["weighted avg"]["recall"]

    return [accuracy, precision, recall, f1_score]

# Store results in a DataFrame
models = {
    "Logistic Regression": best_log,
    "Naive Bayes": best_nb,
    "SVM": best_svm
}
```

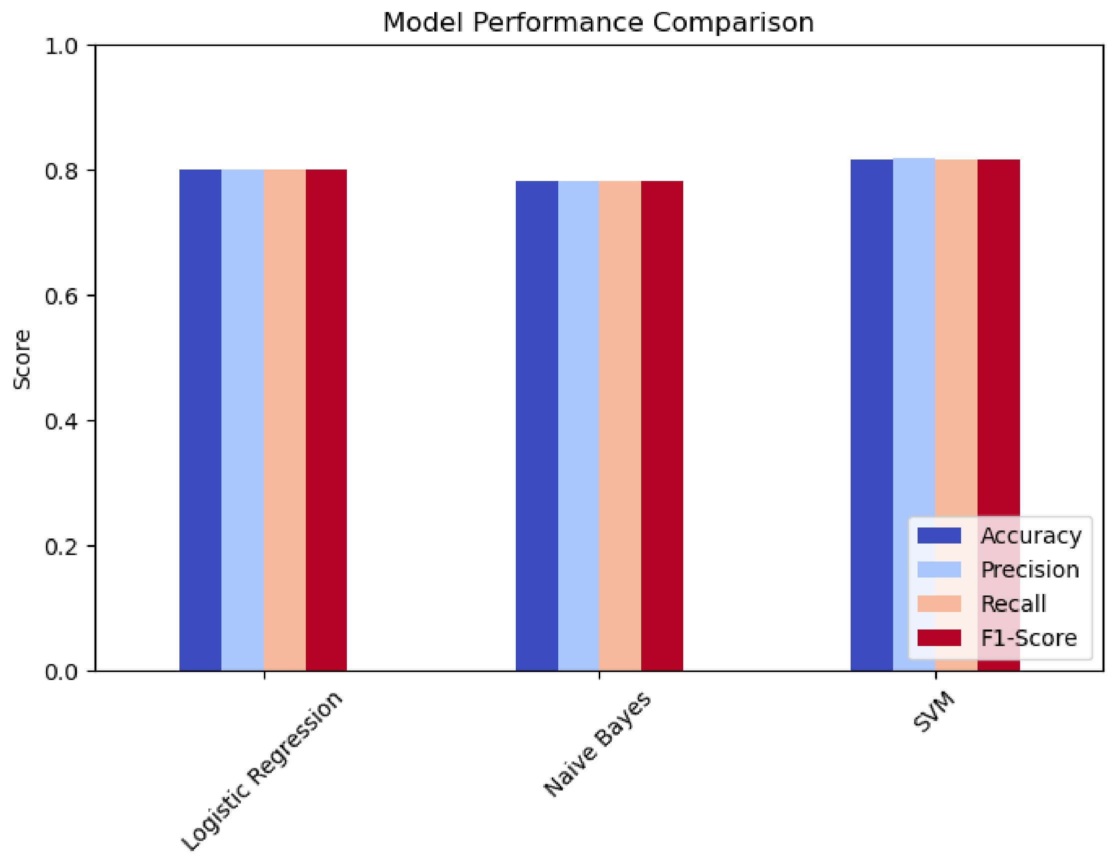
```python
# Store results in a dictionary
results = {name: get_model_metrics(model, X_test, y_test) for name, model in␣
↪models.items()}
df_results = pd.DataFrame(results, index=["Accuracy", "Precision", "Recall",␣
↪"F1-Score"]).T

# Display results
print("\n Model Comparison Table:")
print(df_results)
```

```
 Model Comparison Table:
                     Accuracy  Precision  Recall  F1-Score
Logistic Regression    0.7995   0.800326  0.7995  0.799607
Naive Bayes            0.7818   0.782944  0.7818  0.781951
SVM                    0.8174   0.818213  0.8174  0.817492
```

[93]:
```python
# Select the best model based on highest F1-score
best_model_name = df_results["F1-Score"].idxmax()
print(f"\n Best Model for News Classification: {best_model_name}")
```

```
 Best Model for News Classification: SVM
```

[95]:
```python
df_results.plot(kind="bar", figsize=(8,5), colormap="coolwarm")
plt.title("Model Performance Comparison")
plt.ylabel("Score")
plt.ylim(0, 1)  # Scores range from 0 to 1
plt.xticks(rotation=45)
plt.legend(loc="lower right")
plt.show()
```



5. Final Report and Presentation

1 News Article Classification Project

1.1 1. Introduction

In this project, we developed a machine learning model to classify news articles into categories like Sports, Politics, and Technology. We followed NLP techniques for preprocessing, feature extraction, model training, and evaluation.

1.2 2. Data Collection and Preprocessing

Loaded a labeled dataset of news articles.

Cleaned text data (removing stopwords, punctuation, and lowercasing).

Handled missing data.

Prepared the text for feature extraction.

1.3 3. Feature Extraction

Used TF-IDF vectorization to convert text into numerical features.

Performed Exploratory Data Analysis (EDA) to understand category distributions.

1.4 4. Model Development & Training

Built classification models:

Logistic Regression

Naive Bayes

Support Vector Machine (SVM)

Tuned hyperparameters to improve performance.

Used cross-validation to ensure robust evaluation.

1.5 5. Model Evaluation

Evaluated models using:

Accuracy

F1-Score

Used weighted F1-score for comparison.

1.6 6. Best Model Selection

Compared the performance of different models.

SVM achieved the highest accuracy and F1-score.

Selected SVM as the final model.

1.7 7. Key Findings

NLP techniques effectively classify news articles.

Automated classification helps in efficient content categorization.

Feature extraction (TF-IDF) significantly impacts model performance.

1.8 8. Conclusion

This project demonstrates how machine learning and NLP techniques can be used for text classification, making content management more efficient.

1.9 9. Future Improvements

Experiment with deep learning models (LSTMs, BERT) for better accuracy.

Expand dataset with more categories.

Optimize feature engineering techniques.

Performed Exploratory Data Analysis (EDA) to understand category distributions.

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