VIDEO PESENTATION:
(https://drive.google.com/file/d/1U52O_RgMSRfiveY7qAdrJhthLUke8BVR/view?usp=sharing)

The primary objective of this project is to build a classification model that can automatically
categorize news articles into different predefined categories. The model will be trained using
a labeled dataset of news articles and will output the most likely category (e.g., sports, ## politics, or technology) for any given article.

```
# Import required libraries
import pandas as pd
import numpy as np
import re, string
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 CountVectorizer,
TfidfVectorizer

nltk.download('stopwords')
nltk.download('wordnet')

[nltk_data] Downloading package stopwords to
[nltk_data]     C:\Users\DELL\AppData\Roaming\nltk_data...
[nltk_data]   Package stopwords is already up-to-date!
[nltk_data] Downloading package wordnet to
[nltk_data]     C:\Users\DELL\AppData\Roaming\nltk_data...
[nltk_data]   Package wordnet is already up-to-date!

True
```

1. Data Collection and Preprocessing:

```
# Load dataset (replace with your file path if needed)
df = pd.read_csv("data_news.csv")

# Quick look at the dataset
print("Dataset shape:", df.shape)
print(df.head())

Dataset shape: (50000, 5)
   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
```

```
# Checked for missing values
print("\nMissing values per column:\n", df.isnull().sum())

# Dropped rows with missing text or category
df = df.dropna(subset=['category',
'short_description']).reset_index(drop=True)

# Filled missing keywords with placeholder
df['keywords'] = df['keywords'].fillna("unknown")
```

```
Missing values per column:
 category                0
headline                0
links                   0
short_description       0
keywords             2668
dtype: int64
```

```
# Import necessary NLTK components
stop_words = set(stopwords.words('english'))  # Load English stopwords
to filter out common non-informative words
lemmatizer = WordNetLemmatizer()  # Initialize WordNet lemmatizer to
reduce words to their base form

# Define a text cleaning function
def clean_text(text):
    text = text.lower()                  #Convert all characters to
```

```
lowercase for uniformity
    text = re.sub(r'[^a-z\s]', '', text)  # Remove all non-letter
characters (punctuation, numbers, etc.)
    tokens = text.split()                 # Tokenize the text by
splitting on whitespace
    tokens = [w for w in tokens if w not in stop_words]  # Remove
stopwords from the token list
    tokens = [lemmatizer.lemmatize(w) for w in tokens]  # Lemmatize
each token to its root form
    return " ".join(tokens)                             # Rejoin the
cleaned tokens into a single string

# Apply the cleaning function to the 'short_description' column
df['clean_text'] = df['short_description'].apply(clean_text)

# Optionally combine 'headline' and 'short_description' for richer
context, then clean
df['combined_text'] = (df['headline'].fillna('') + " " +
df['short_description']).apply(clean_text)

# Preview the cleaned output alongside original category and
description
df[['category', 'short_description', 'clean_text']].head()
```

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

                                          clean_text
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...
```

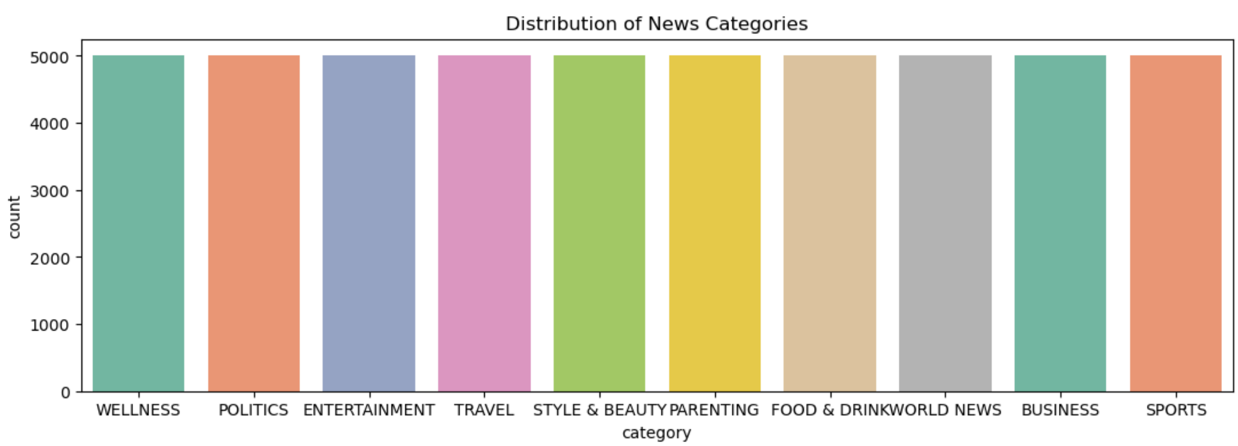
2. Feature Extraction

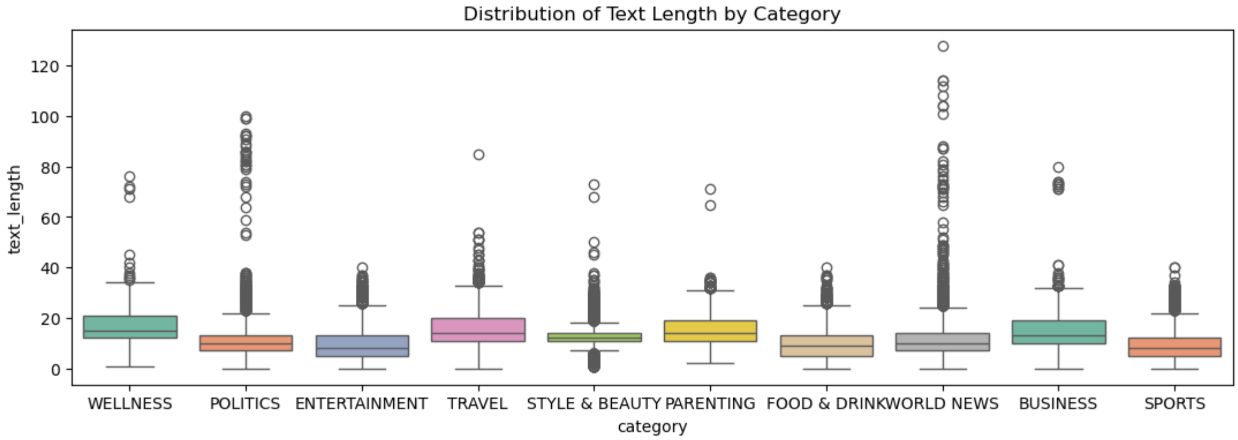
```
## Bag-of-Words vectorization: captures word frequency for unigrams
(single words)
bow_vectorizer = CountVectorizer(max_features=5000, ngram_range=(1,1))
# Limit to top 5000 most frequent unigrams
X_bow = bow_vectorizer.fit_transform(df['clean_text'])  # Transform
cleaned text into sparse matrix of word counts

# TF-IDF vectorization: captures term importance using unigrams and
bigrams (single words + two-word phrases)
```

```
tfidf_vectorizer = TfidfVectorizer(max_features=5000,
ngram_range=(1,2))  # Limit to top 5000 features including bigrams
X_tfidf = tfidf_vectorizer.fit_transform(df['clean_text'])  #
Transform cleaned text into weighted matrix of term importance

# Print the shape of resulting feature matrices
print("BoW shape:", X_bow.shape)       # Output: (number of samples,
number of features)
print("TF-IDF shape:", X_tfidf.shape)  # Output: (number of samples,
number of features)
```

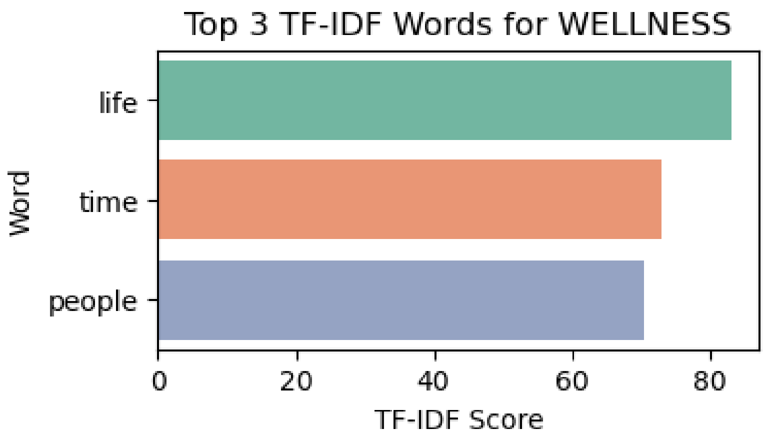
```
BoW shape: (50000, 5000)
TF-IDF shape: (50000, 5000)
```

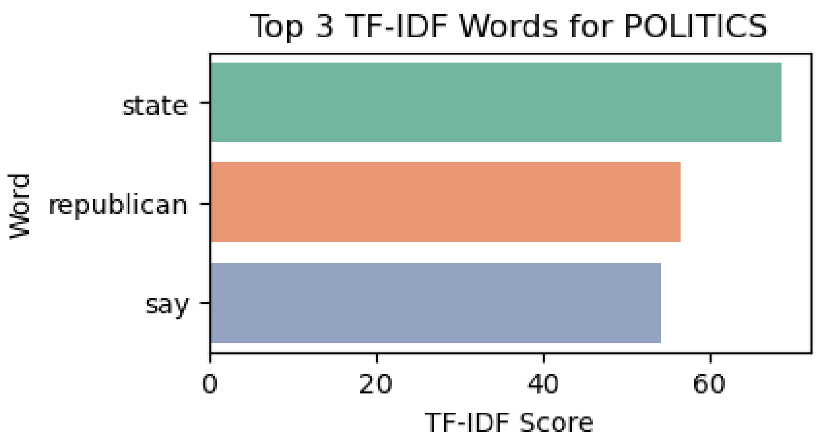
```
# Plot the count of articles per category
plt.figure(figsize=(13,4))
sns.countplot(data=df, x='category', hue='category', palette="Set2",
legend=False)  # Count plot with colored bars per category
plt.title("Distribution of News Categories")
plt.show()

# Calculate text length (number of words) for each cleaned description
df['text_length'] = df['clean_text'].apply(lambda x: len(x.split()))

# Plot boxplot of text length distribution across categories
plt.figure(figsize=(13,4))
sns.boxplot(data=df, x='category', y='text_length', hue='category',
palette="Set2", legend=False)  # Boxplot showing spread of word counts
plt.title("Distribution of Text Length by Category")
plt.show()
```

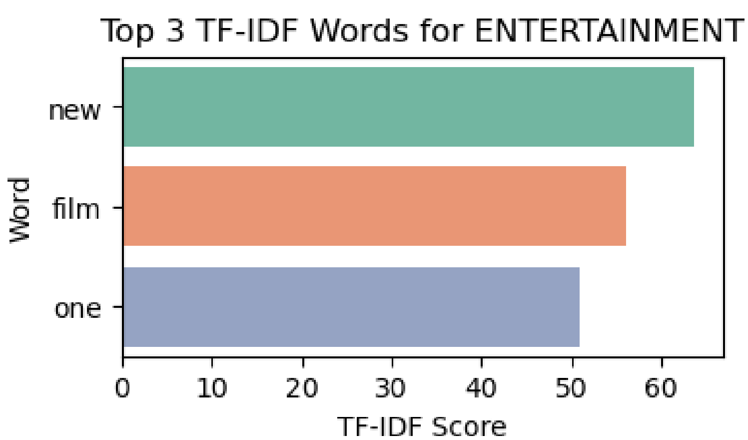


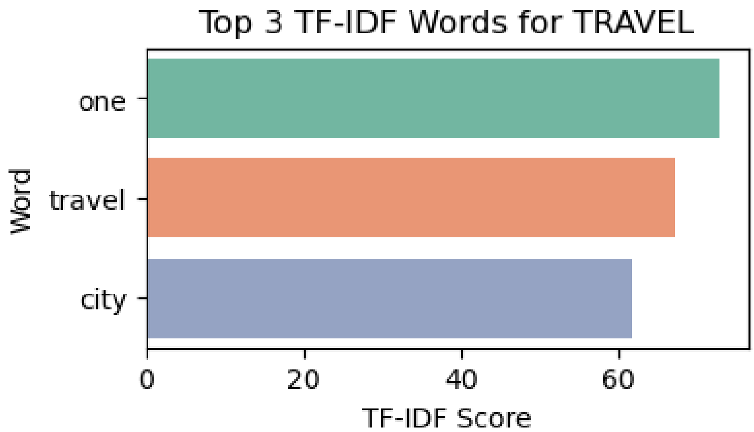



```
#function for top words
def plot_top_tfidf_words(category, top_n=10):
    # Filter rows for this category
    texts = df[df['category']==category]['clean_text']

    # Fit TF-IDF on this subset
    tfidf = TfidfVectorizer(max_features=5000, ngram_range=(1,2))
    X = tfidf.fit_transform(texts)

    # Sum TF-IDF scores across all docs
    scores = np.asarray(X.sum(axis=0)).flatten()
    top_indices = scores.argsort()[::-1][:top_n]
    top_words = [tfidf.get_feature_names_out()[i] for i in
top_indices]
    top_scores = [scores[i] for i in top_indices]

    # Plot
    plt.figure(figsize=(4,2))
    sns.barplot(x=top_scores, y=top_words,
hue=top_words,palette="Set2", legend=False)

    plt.title(f"Top {top_n} TF-IDF Words for {category}")
    plt.xlabel("TF-IDF Score")
    plt.ylabel("Word")
    plt.show()

# Example: plot for each category
for cat in df['category'].unique():
    plot_top_tfidf_words(cat, top_n=3)
```

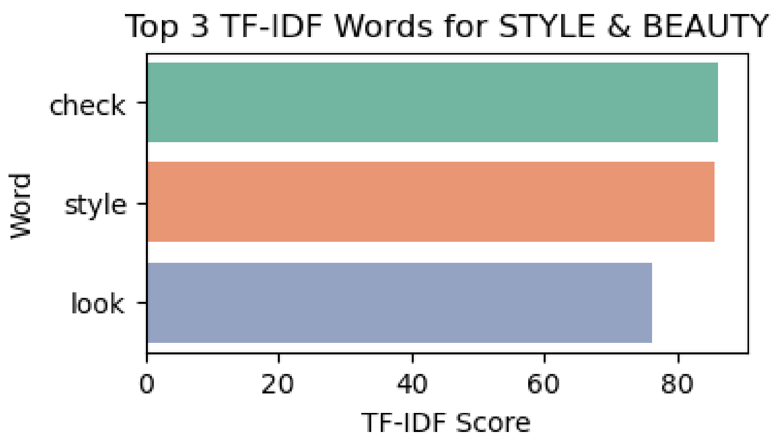

Top 3 TF-IDF Words for WELLNESS
life
time
people
Word
0
20
40
60
80
TF-IDF Score


Top 3 TF-IDF Words for POLITICS
state
republican
say
Word
0
20
40
60
TF-IDF Score

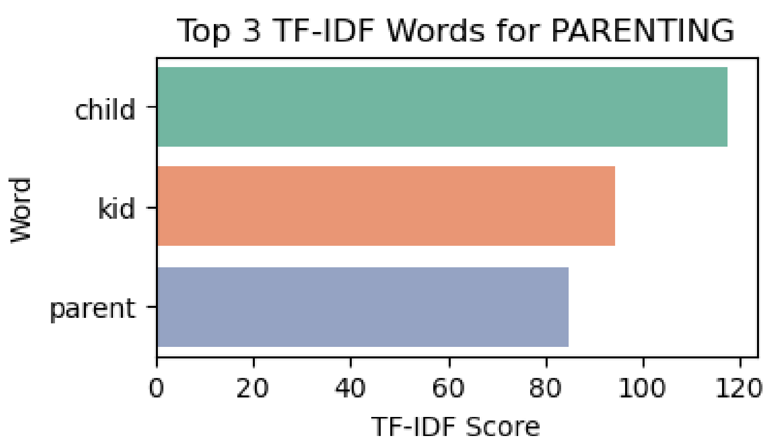

Top 3 TF-IDF Words for ENTERTAINMENT
new
film
one
Word
0
10
20
30
40
50
60
TF-IDF Score



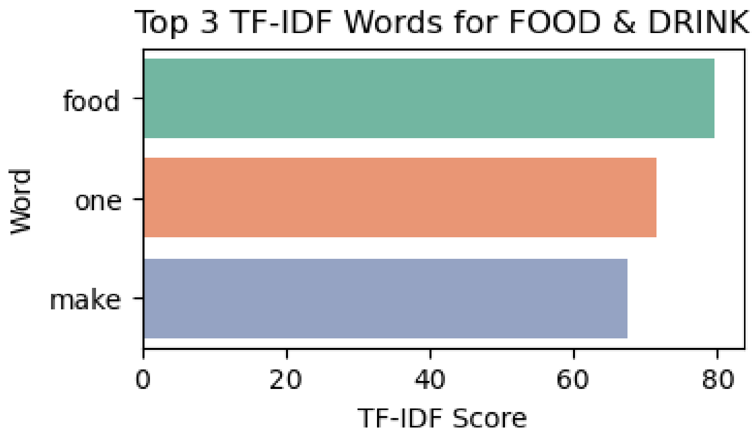
Top 3 TF-IDF Words for TRAVEL
one
travel
city
Word
0
20
40
60
TF-IDF Score

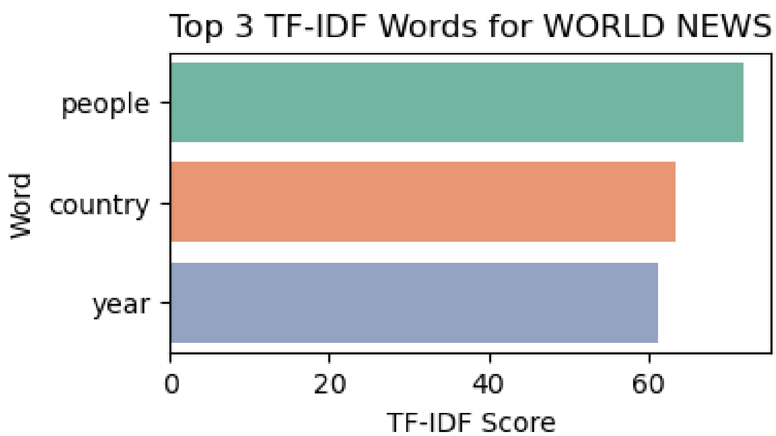


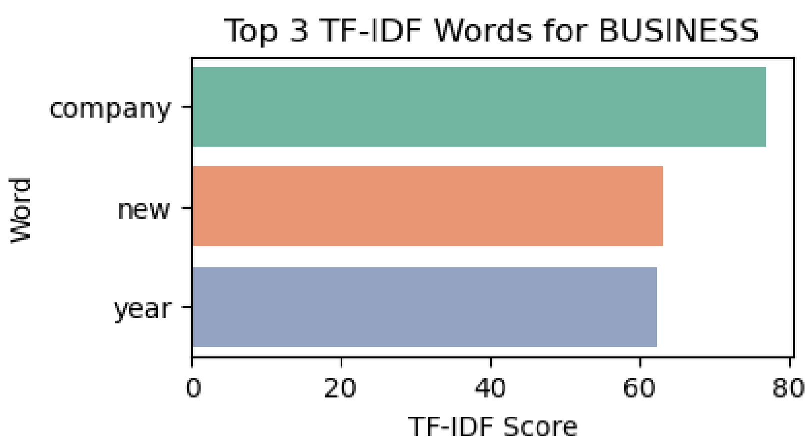
Top 3 TF-IDF Words for STYLE & BEAUTY
check
style
look
Word
0
20
40
60
80
TF-IDF Score

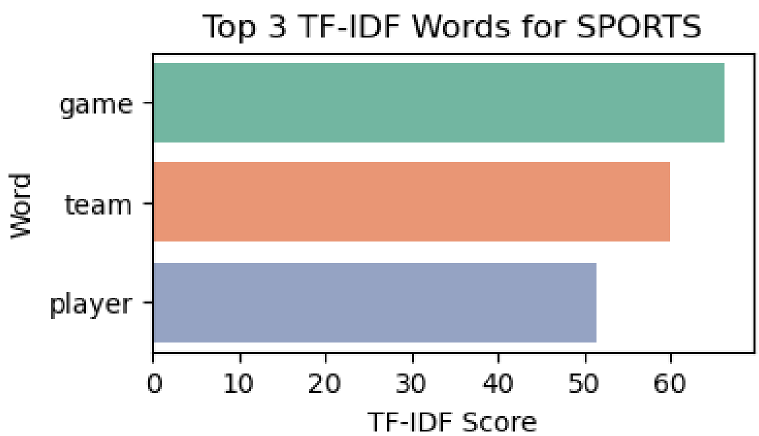


Top 3 TF-IDF Words for PARENTING
child
kid
parent
Word
0
20
40
60
80
100
120
TF-IDF Score


Top 3 TF-IDF Words for FOOD & DRINK
food
one
make
Word
0
20
40
60
80
TF-IDF Score


Top 3 TF-IDF Words for WORLD NEWS
people
country
year
Word
0
20
40
60
TF-IDF Score


Top 3 TF-IDF Words for BUSINESS
company
new
year
Word
0
20
40
60
80
TF-IDF Score

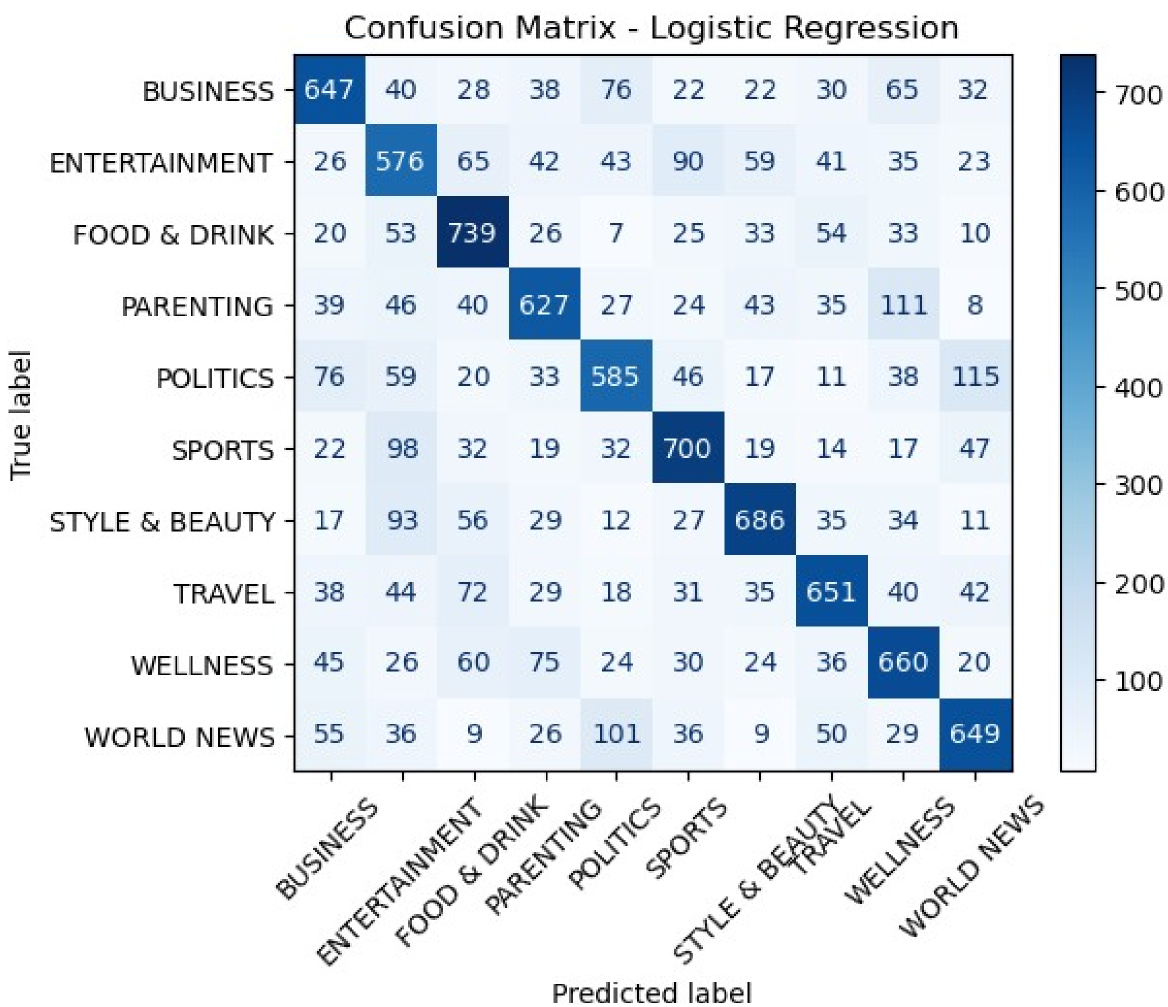


3. Model Development and Training with Evaluation

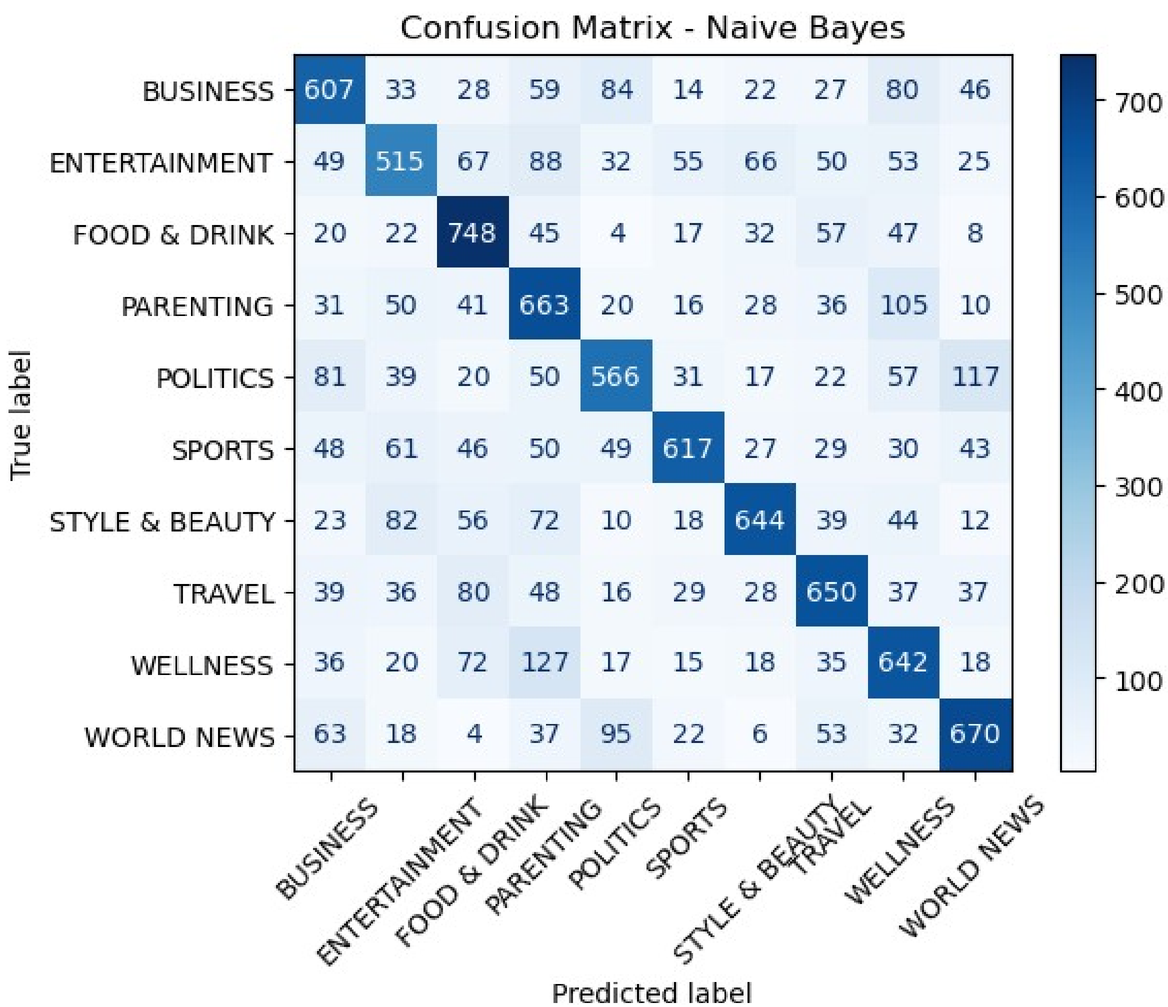
```
from sklearn.linear_model import LogisticRegression
from sklearn.naive_bayes import MultinomialNB
from sklearn.svm import LinearSVC
from sklearn.metrics import (
    accuracy_score, precision_score, recall_score, f1_score,
    classification_report, confusion_matrix, ConfusionMatrixDisplay
)
from sklearn.model_selection import train_test_split, cross_val_score


# □ Split the dataset into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(
    X_tfidf,                        # TF-IDF features from previous step
    df['category'],                 # Target labels (news categories)
    test_size=0.2,                  # Reserve 20% of data for testing
    stratify=df['category'],        # Ensure balanced category
distribution
    random_state=42                 # Set seed for reproducibility
)

# □ Define classification models
models = {
    "Logistic Regression": LogisticRegression(max_iter=500, C=1.0),
    "Naive Bayes": MultinomialNB(alpha=1.0),
    "SVM": LinearSVC(C=1.0)
}

# □ Train, evaluate, and visualize each model
results = []  # Store evaluation metrics

for name, model in models.items():
    print(f"\n□ Training and evaluating {name}...")

    model.fit(X_train, y_train)  # Train model
```

```
    y_pred = model.predict(X_test)  # Predict on test set

    # Compute evaluation metrics
    acc = accuracy_score(y_test, y_pred)
    prec = precision_score(y_test, y_pred, average='macro')
    rec = recall_score(y_test, y_pred, average='macro')
    f1 = f1_score(y_test, y_pred, average='macro')

    print(classification_report(y_test, y_pred))  # Detailed report

    # Cross-validation for robustness
    cv_scores = cross_val_score(model, X_tfidf, df['category'], cv=5,
scoring='f1_macro')

    # Store results
    results.append({
        "Model": name,
        "Accuracy": acc,
        "Precision": prec,
        "Recall": rec,
        "F1-score": f1,
        "CV Mean F1": cv_scores.mean()
    })

    # Confusion matrix visualization
    cm = confusion_matrix(y_test, y_pred, labels=model.classes_)
    disp = ConfusionMatrixDisplay(confusion_matrix=cm,
display_labels=model.classes_)
    disp.plot(cmap="Blues", xticks_rotation=45)
    plt.title(f"Confusion Matrix - {name}")
    plt.show()

# □ Compare model performance
results_df = pd.DataFrame(results)
print("\n□ Model Comparison:\n", results_df)

#Visual comparison using bar chart
results_df.set_index("Model")[["Accuracy","F1-score"]].plot(
    kind="bar", figsize=(8,5), colormap="Set2"
)
plt.title("Model Performance Comparison")
plt.ylabel("Score")
plt.ylim(0,1)
plt.grid(axis='y', linestyle='--', alpha=0.5)  # Add horizontal
gridlines
plt.xticks(rotation=0)
plt.tight_layout()
plt.show()
```

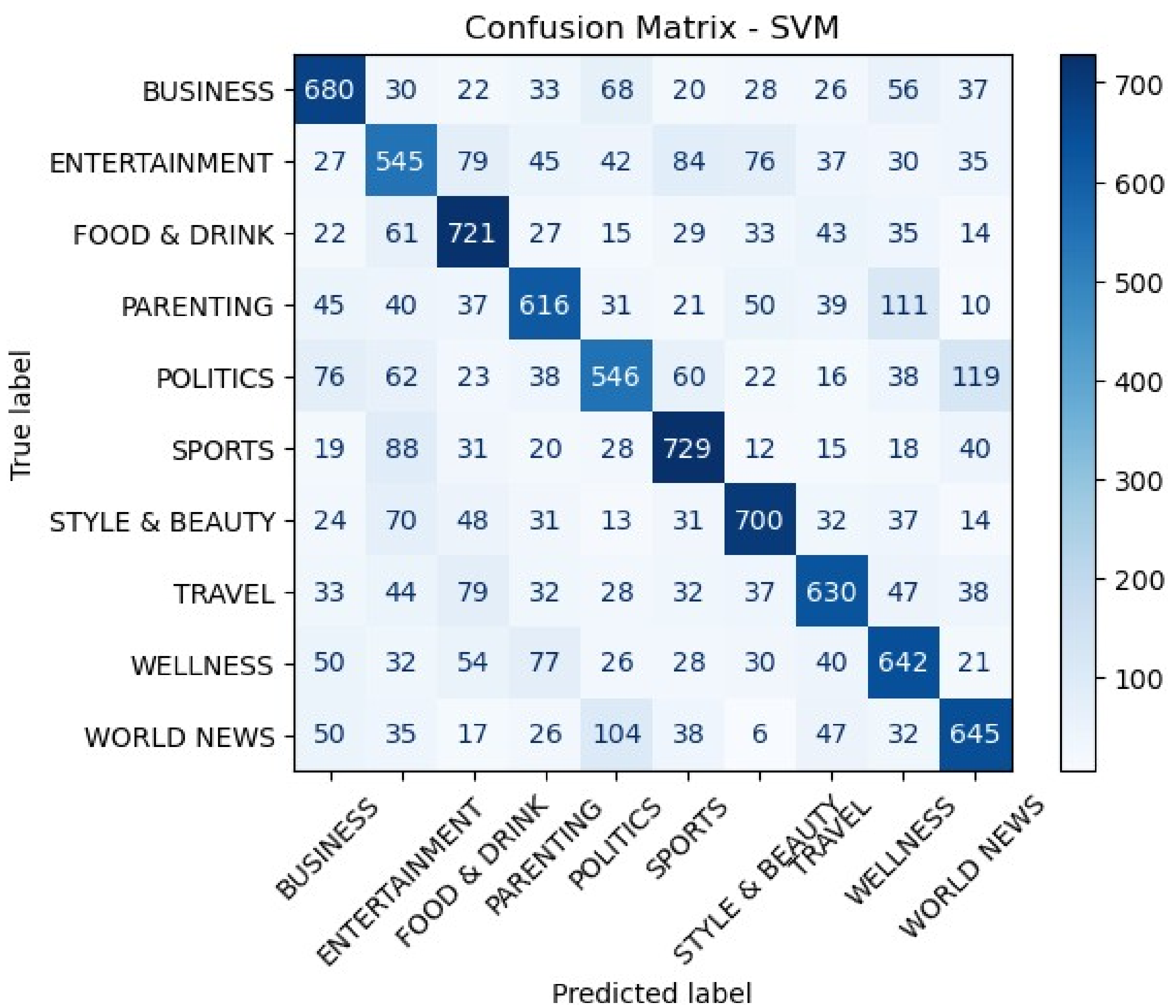
```
□ Training and evaluating Logistic Regression...
                precision    recall  f1-score   support

      BUSINESS       0.66      0.65      0.65      1000
 ENTERTAINMENT       0.54      0.58      0.56      1000
  FOOD & DRINK       0.66      0.74      0.70      1000
     PARENTING       0.66      0.63      0.65      1000
      POLITICS       0.63      0.58      0.61      1000
        SPORTS       0.68      0.70      0.69      1000
STYLE & BEAUTY       0.72      0.69      0.70      1000
        TRAVEL       0.68      0.65      0.67      1000
      WELLNESS       0.62      0.66      0.64      1000
    WORLD NEWS       0.68      0.65      0.66      1000

      accuracy                           0.65     10000
     macro avg       0.65      0.65      0.65     10000
  weighted avg       0.65      0.65      0.65     10000
```



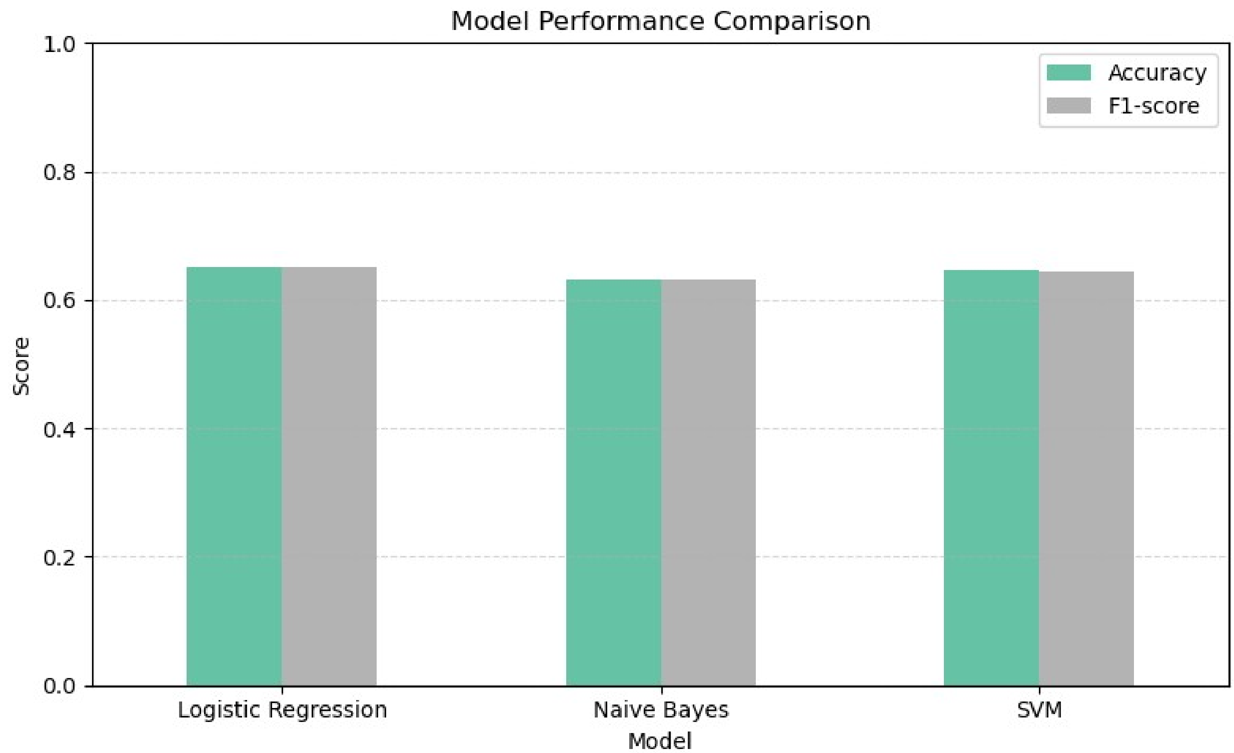
```
□ Training and evaluating Naive Bayes...
                precision    recall  f1-score   support

      BUSINESS       0.61      0.61      0.61      1000
 ENTERTAINMENT       0.59      0.52      0.55      1000
  FOOD & DRINK       0.64      0.75      0.69      1000
     PARENTING       0.54      0.66      0.59      1000
      POLITICS       0.63      0.57      0.60      1000
        SPORTS       0.74      0.62      0.67      1000
STYLE & BEAUTY       0.73      0.64      0.68      1000
        TRAVEL       0.65      0.65      0.65      1000
      WELLNESS       0.57      0.64      0.60      1000
    WORLD NEWS       0.68      0.67      0.67      1000

      accuracy                           0.63     10000
     macro avg       0.64      0.63      0.63     10000
  weighted avg       0.64      0.63      0.63     10000
```



```
□ Training and evaluating SVM...
                precision    recall  f1-score   support

      BUSINESS       0.66      0.68      0.67      1000
 ENTERTAINMENT       0.54      0.55      0.54      1000
  FOOD & DRINK       0.65      0.72      0.68      1000
     PARENTING       0.65      0.62      0.63      1000
      POLITICS       0.61      0.55      0.57      1000
        SPORTS       0.68      0.73      0.70      1000
STYLE & BEAUTY       0.70      0.70      0.70      1000
        TRAVEL       0.68      0.63      0.65      1000
      WELLNESS       0.61      0.64      0.63      1000
    WORLD NEWS       0.66      0.65      0.65      1000

      accuracy                           0.65     10000
     macro avg       0.65      0.65      0.64     10000
  weighted avg       0.65      0.65      0.64     10000
```



```
□ Model Comparison:
                  Model  Accuracy  Precision  Recall  F1-score  CV
Mean F1
0  Logistic Regression    0.6520   0.653375  0.6520  0.652055
0.635765
1          Naive Bayes    0.6322   0.637487  0.6322  0.632322
0.620575
2                  SVM    0.6454   0.645280  0.6454  0.644703
0.613905
```



Insights:

THANK YOU