🤖 NewsBot Intelligence System

ITAI 2373 - Mid-Term Group Project Template

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🎯 Project Overview

Welcome to your NewsBot Intelligence System! This notebook will guide you through building a comprehensive NLP system that:

- 📰 **Processes** news articles with advanced text cleaning
- 🏷️ **Classifies** articles into categories (Politics, Sports, Technology, Business, Entertainment, Health)
- 🔍 **Extracts** named entities (people, organizations, locations, dates, money)
- 😊 **Analyzes** sentiment and emotional tone
- 📊 **Generates** insights for business intelligence

📚 Module Integration Checklist

- [ ] **Module 1:** NLP applications and real-world context
- [ ] **Module 2:** Text preprocessing pipeline
- [ ] **Module 3:** TF-IDF feature extraction
- [ ] **Module 4:** POS tagging analysis
- [ ] **Module 5:** Syntax parsing and semantic analysis
- [ ] **Module 6:** Sentiment and emotion analysis
- [ ] **Module 7:** Text classification system
- [ ] **Module 8:** Named Entity Recognition

📦 Setup and Installation

Let's start by installing and importing all the libraries we'll need for our NewsBot system.

```
# Install required packages (run this cell first!)
!pip install spacy scikit-learn nltk pandas matplotlib seaborn wordcloud plotly
!python -m spacy download en_core_web_sm

# Download NLTK data
import nltk
```

```
nltk.download('punkt')
nltk.download('stopwords')
nltk.download('wordnet')
nltk.download('vader_lexicon')
nltk.download('averaged_perceptron_tagger')
nltk.download('punkt_tab')
nltk.download('averaged_perceptron_tagger_eng') # Added this line for POS tagger

print("✅ All packages installed successfully!")
```

```
Requirement already satisfied: contourpy>=1.0.1 in /usr/local/lib/python3.11/dist-packages (from matplotlib) (1.3.2)
Requirement already satisfied: cycler>=0.10 in /usr/local/lib/python3.11/dist-packages (from matplotlib) (0.12.1)
Requirement already satisfied: fonttools>=4.22.0 in /usr/local/lib/python3.11/dist-packages (from matplotlib) (4.59.0)
Requirement already satisfied: kiwisolver>=1.3.1 in /usr/local/lib/python3.11/dist-packages (from matplotlib) (1.4.8)
Requirement already satisfied: pillow>=8 in /usr/local/lib/python3.11/dist-packages (from matplotlib) (11.3.0)
Requirement already satisfied: pyparsing>=2.3.1 in /usr/local/lib/python3.11/dist-packages (from matplotlib) (3.2.3)
Requirement already satisfied: tenacity>=6.2.0 in /usr/local/lib/python3.11/dist-packages (from plotly) (8.5.0)
```

```
[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 vader_lexicon to /root/nltk_data...
[nltk_data]   Package vader_lexicon is already up-to-date!
[nltk_data] Downloading package averaged_perceptron_tagger to
[nltk_data]     /root/nltk_data...
[nltk_data]   Package averaged_perceptron_tagger is already up-to-
[nltk_data]       date!
[nltk_data] Downloading package punkt_tab to /root/nltk_data...
[nltk_data]   Package punkt_tab is already up-to-date!
[nltk_data] Downloading package averaged_perceptron_tagger_eng to
[nltk_data]     /root/nltk_data...
[nltk_data]   Package averaged_perceptron_tagger_eng is already up-to-
[nltk_data]       date!
```

```
# Import all necessary libraries
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from wordcloud import WordCloud
import plotly.express as px
import plotly.graph_objects as go
from collections import Counter, defaultdict
import re
import warnings
warnings.filterwarnings('ignore')

# NLP Libraries
import spacy
import nltk
from nltk.corpus import stopwords
from nltk.tokenize import word_tokenize, sent_tokenize
from nltk.stem import WordNetLemmatizer
from nltk.sentiment import SentimentIntensityAnalyzer
from nltk.tag import pos_tag

# Scikit-learn for machine learning
from sklearn.feature_extraction.text import TfidfVectorizer, CountVectorizer
from sklearn.model_selection import train_test_split, cross_val_score
from sklearn.naive_bayes import MultinomialNB
from sklearn.svm import SVC
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import classification_report, confusion_matrix, accuracy_score
from sklearn.pipeline import Pipeline

# Load spaCy model
nlp = spacy.load('en_core_web_sm')
```

```
# Set up plotting style
plt.style.use('default')
sns.set_palette("husl")

print("📚 All libraries imported successfully!")
print(f"🔧 spaCy model loaded: {nlp.meta['name']} v{nlp.meta['version']}")
```

```
📚 All libraries imported successfully!
🔧 spaCy model loaded: core_web_sm v3.8.0
```

📊 Data Loading and Exploration

🎯 Module 1: Understanding Our NLP Application

Before we dive into the technical implementation, let's understand the real-world context of our NewsBot Intelligence System. This system addresses several business needs:

1. **Media Monitoring:** Automatically categorize and track news coverage
2. **Business Intelligence:** Extract key entities and sentiment trends
3. **Content Management:** Organize large volumes of news content
4. **Market Research:** Understand public sentiment about topics and entities

💡 **Discussion Question:** What other real-world applications can you think of for this type of system? Consider different industries and use cases.

-Weather analyst can utilize this tyoe of system to have a better way of informing the public on newer weather patterns along with how to properly prepare. By analyzing different communities reactions and analyzing the data of damages, these experts can better understand what can save a life in a situation versus something that could be a death sentence.

```
# Step 1: Install Kaggle API
%pip install kaggle

# Step 2: Upload your kaggle.json file
from google.colab import userdata
print("Please upload your kaggle.json file:")
userdata.get('KAGGLE_API_KEY')
print("✅ Kaggle API setup complete!")

# Step 3: Set up API credentials
!mkdir -p ~/.kaggle
!cp kaggle.json ~/.kaggle/
!chmod 600 ~/.kaggle/kaggle.json
```

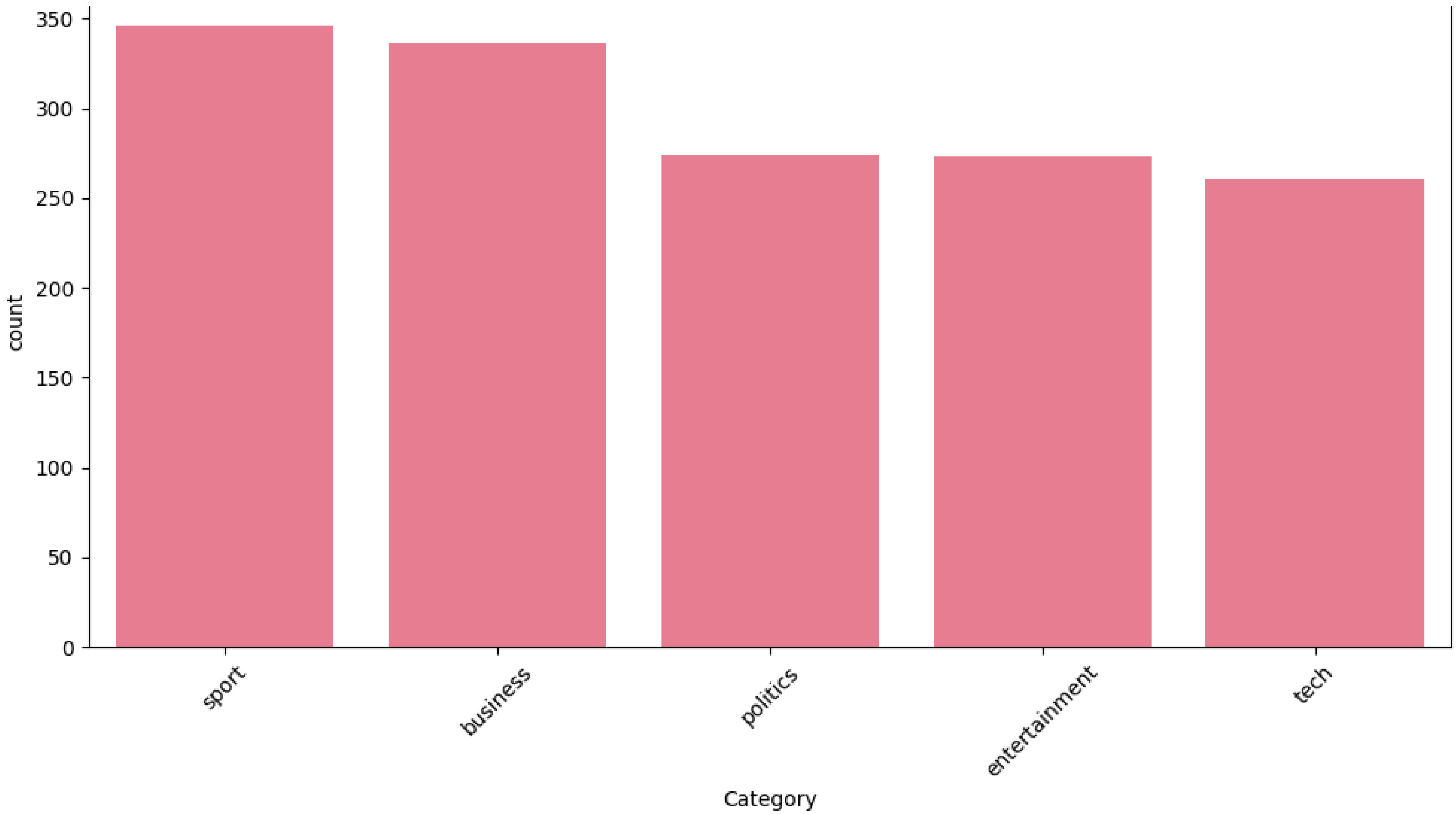
```
# Download BBC News Dataset
!kaggle competitions download -c learn-ai-bbc
print("✅ BBC News Dataset downloaded!")

# Unzip the files
!unzip learn-ai-bbc.zip

# List the files to see what we have
!ls -la

# Load the dataset
import pandas as pd
import os

# Check what files are available
print("Available files:")
for file in os.listdir('.'):
    if file.endswith('.csv'):
        print(f"  - {file}")

# Load the main dataset
df = pd.read_csv('BBC News Train.csv')  #filename
print(f"Dataset shape: {df.shape}")
print(f"Columns: {df.columns.tolist()}") # Corrected 'column' to 'columns'
print(f"Categories: {df['Category'].unique()}")
```

```
Requirement already satisfied: kaggle in /usr/local/lib/python3.11/dist-packages (1.7.4.5)
Requirement already satisfied: bleach in /usr/local/lib/python3.11/dist-packages (from kaggle) (6.2.0)
Requirement already satisfied: certifi>=14.05.14 in /usr/local/lib/python3.11/dist-packages (from kaggle) (2025.7.14)
Requirement already satisfied: charset-normalizer in /usr/local/lib/python3.11/dist-packages (from kaggle) (3.4.2)
Requirement already satisfied: idna in /usr/local/lib/python3.11/dist-packages (from kaggle) (3.10)
Requirement already satisfied: protobuf in /usr/local/lib/python3.11/dist-packages (from kaggle) (5.29.5)
Requirement already satisfied: python-dateutil>=2.5.3 in /usr/local/lib/python3.11/dist-packages (from kaggle) (2.9.0.post0)
Requirement already satisfied: python-slugify in /usr/local/lib/python3.11/dist-packages (from kaggle) (8.0.4)
Requirement already satisfied: requests in /usr/local/lib/python3.11/dist-packages (from kaggle) (2.32.3)
Requirement already satisfied: setuptools>=21.0.0 in /usr/local/lib/python3.11/dist-packages (from kaggle) (75.2.0)
Requirement already satisfied: six>=1.10 in /usr/local/lib/python3.11/dist-packages (from kaggle) (1.17.0)
Requirement already satisfied: text-unidecode in /usr/local/lib/python3.11/dist-packages (from kaggle) (1.3)
Requirement already satisfied: tqdm in /usr/local/lib/python3.11/dist-packages (from kaggle) (4.67.1)
Requirement already satisfied: urllib3>=1.15.1 in /usr/local/lib/python3.11/dist-packages (from kaggle) (2.5.0)
Requirement already satisfied: webencodings in /usr/local/lib/python3.11/dist-packages (from kaggle) (0.5.1)
Please upload your kaggle.json file:
✅ Kaggle API setup complete!
learn-ai-bbc.zip: Skipping, found more recently modified local copy (use --force to force download)
✅ BBC News Dataset downloaded!
Archive:  learn-ai-bbc.zip
replace BBC News Sample Solution.csv? [y]es, [n]o, [A]ll, [N]one, [r]ename: Y
  inflating: BBC News Sample Solution.csv
replace BBC News Test.csv? [y]es, [n]o, [A]ll, [N]one, [r]ename: A
```

```
  inflating: BBC News Test.csv
  inflating: BBC News Train.csv
total 6876
drwxr-xr-x 1 root root    4096 Aug  5 00:39  .
drwxr-xr-x 1 root root    4096 Aug  4 23:34  ..
-rw-r--r-- 1 root root   10369 Dec  2  2019 'BBC News Sample Solution.csv'
-rw-r--r-- 1 root root 1712432 Dec  2  2019 'BBC News Test.csv'
-rw-r--r-- 1 root root 3351206 Dec  2  2019 'BBC News Train.csv'
drwxr-xr-x 4 root root    4096 Jul 29 13:36  .config
-rw-r--r-- 1 root root      66 Aug  4 23:46  kaggle.json
-rw-r--r-- 1 root root 1936538 Dec  2  2019  learn-ai-bbc.zip
drwxr-xr-x 1 root root    4096 Jul 29 13:36  sample_data
Available files:
  - BBC News Train.csv
  - BBC News Sample Solution.csv
  - BBC News Test.csv
Dataset shape: (1490, 3)
Columns: ['ArticleId', 'Text', 'Category']
Categories: ['business' 'tech' 'politics' 'sport' 'entertainment']
```

```
# Basic dataset exploration
print("📊 OVERVIEW OF DATA")
print("=" * 50)
print(f"Total articles: {len(df)}")
print(f"Unique categories: {df['Category'].nunique()}")
print(f"Categories: {df['Category'].unique().tolist()}")
# print(f"Date range: {df['Date'].min()} to {df['Date'].max()}") # Removed as 'Date' column not present
# print(f"Unique sources: {df['Source'].nunique()}") # Removed as 'Source' column not present

print("\n📈 CATEGORY DISTRIBUTION")
print("=" * 50)
category_counts = df['Category'].value_counts() # Corrected 'category' to 'Category'
print(category_counts)

# Visualize category distribution
plt.figure(figsize=(10, 6))
sns.countplot(data=df, x='Category', order=category_counts.index) # Corrected 'category' to 'Category'
plt.title('Distribution of News Categories')
plt.xticks(rotation=45)
plt.tight_layout()
plt.show()

#Check for missing value
print("\n🔍 MISSING VALUES")
print("=" * 50)
print(df.isnull().sum())

#Text Length Distribution
print("\n📝 TEXT LENGTH DISTRIBUTION")
```

```
print("=" * 50)
df['Text_Length'] = df['Text'].apply(len)
plt.figure(figsize=(10, 6))
sns.histplot(df['Text_Length'], bins=50, kde=True)
plt.title('Distribution of Text Lengths')
plt.xlabel('Word Count')
plt.ylabel('Frequency')
plt.tight_layout()
plt.show()

#Data quality
print("\n🔍 DATA QUALITY")
print("=" * 50)
print(f"Duplicate articles: {df.duplicated().sum()}")
```

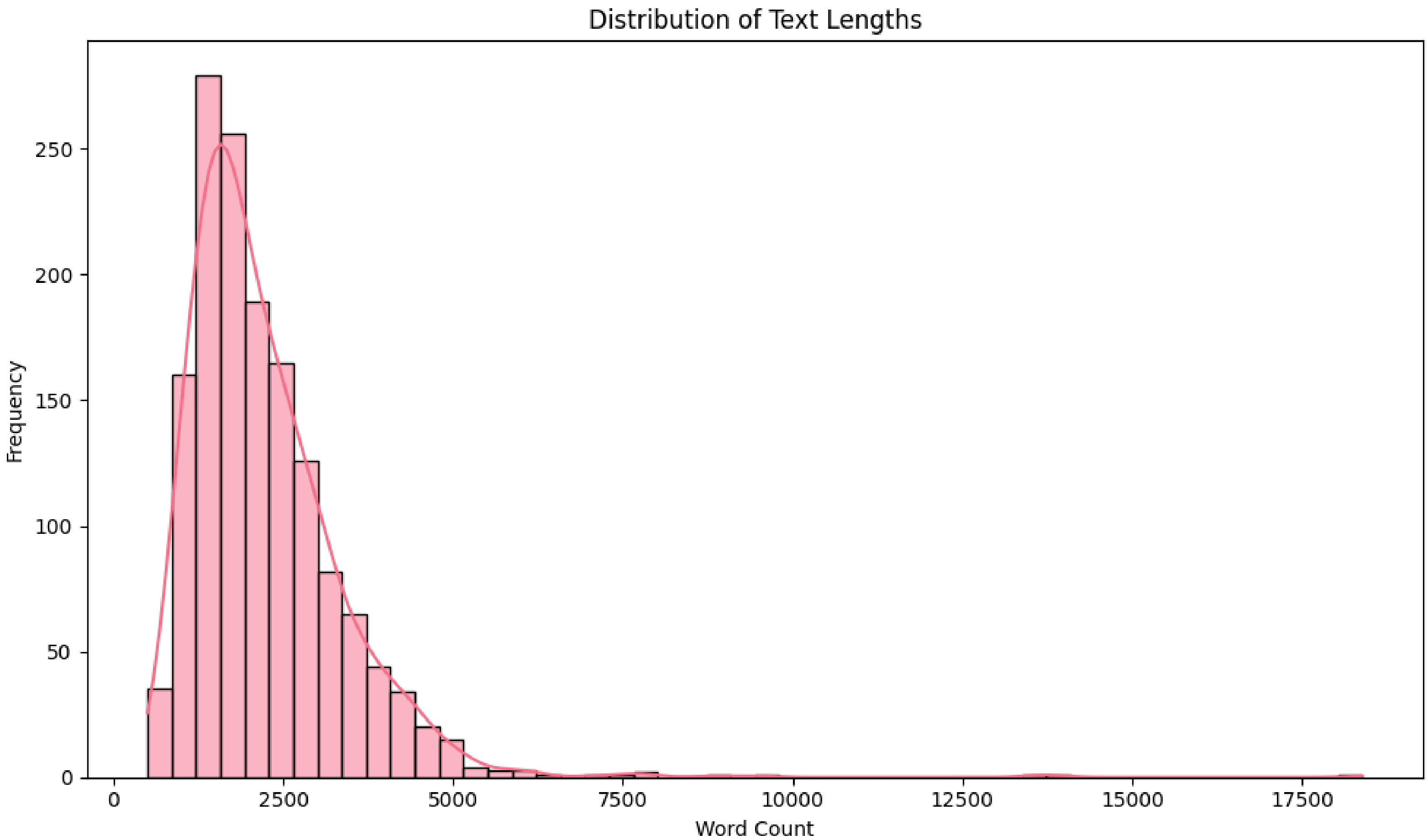


🔍 MISSING VALUES
==
ArticleId   0

```
Text        0
Category    0
dtype: int64
```

📝 TEXT LENGTH DISTRIBUTION

```
==================================================
```



🔍 DATA QUALITY

```
==================================================
Duplicate articles: 0
```

🧹 Text Preprocessing Pipeline

🎯 Module 2: Advanced Text Preprocessing

Now we'll implement a comprehensive text preprocessing pipeline that cleans and normalizes our news articles. This is crucial for all downstream NLP tasks.

Key Preprocessing Steps:

1. **Text Cleaning:** Remove HTML, URLs, special characters
2. **Tokenization:** Split text into individual words
3. **Normalization:** Convert to lowercase, handle contractions
4. **Stop Word Removal:** Remove common words that don't carry meaning
5. **Lemmatization:** Reduce words to their base form

💡 **Think About:** Why is preprocessing so important? What happens if we skip these steps?

```
# Initialize preprocessing tools
lemmatizer = WordNetLemmatizer()
stop_words = set(stopwords.words('english'))

def clean_text(text):


    """
    Comprehensive text cleaning function

    💡 TIP: This function should handle:
    - HTML tags and entities
    - URLs and email addresses
    - Special characters and numbers
    - Extra whitespace
    """
    if pd.isna(text):
        return ""

    # Convert to string and lowercase
    text = str(text).lower()

    # 🚀 YOUR CODE HERE: Implement text cleaning
    # Remove HTML tags
    text = re.sub(r'<[^>]+>', '', text)

    # Remove URLs
```

```python
    text = re.sub(r'http\S+|www\S+|https\S+', '', text, flags=re.MULTILINE)

    # Remove email addresses
    text = re.sub(r'\S+@\S+', '', text)

    # Remove special characters and digits (keep only letters and spaces)
    text = re.sub(r'[^a-zA-Z\s]', '', text)

    # Remove extra whitespace
    text = re.sub(r'\s+', ' ', text).strip()

    return text

def preprocess_text(text, remove_stopwords=True, lemmatize=True):
    """
    Complete preprocessing pipeline


    """
    # Clean text
    text = clean_text(text)

    if not text:
        return ""

    # 🚀 Implement tokenization and preprocessing
    # Tokenize
    tokens = word_tokenize(text)

    # Remove stop words if requested
    if remove_stopwords:
        tokens = [token for token in tokens if token not in stop_words]

    # Lemmatize if requested
    if lemmatize:
        tokens = [lemmatizer.lemmatize(token) for token in tokens]

    # Filter out very short words
    tokens = [token for token in tokens if len(token) > 2]

    return ' '.join(tokens)

# Test the preprocessing function
sample_text = "bbc poll indicates economic gloom citizens in a majority of nations surveyed in a bbc world service ..."
print("Original text:")
print(sample_text)
print("\nCleaned text:")
print(clean_text(sample_text))
```

```python
print("\nFully preprocessed text:")
print(preprocess_text(sample_text))
```

```
Original text:
bbc poll indicates economic gloom citizens in a majority of nations surveyed in a bbc world service ...

Cleaned text:
bbc poll indicates economic gloom citizens in a majority of nations surveyed in a bbc world service

Fully preprocessed text:
bbc poll indicates economic gloom citizen majority nation surveyed bbc world service
```

```python
# Apply preprocessing to the dataset
print("🧹 Preprocessing all articles...")

# Create new columns for processed text
df['text_clean'] = df['Text'].apply(clean_text)
df['text_processed'] = df['Text'].apply(preprocess_text)

# Combine title and content for full article analysis
df['full_text'] = df['Text'].fillna('')
df['full_text_processed'] = df['text_processed']

print("✅ Preprocessing complete!")

# Show before and after examples
print("\n📝 BEFORE AND AFTER EXAMPLES")
print("=" * 60)
for i in range(min(3, len(df))):
    print(f"\nExample {i+1}:")
    print(f"Original: {df.iloc[i]['full_text'][:100]}...")
    print(f"Processed: {df.iloc[i]['full_text_processed'][:100]}...")

#Calculate average text length before and after
df['original_text_length'] = df['full_text'].str.len()
df['processed_text_length'] = df['full_text_processed'].str.len()

#Visualize text length before and after
plt.figure(figsize=(10,5))
sns.histplot(df['original_text_length'], bins=50, kde=True, label='Original', color='blue')
sns.histplot(df['processed_text_length'], bins=50, kde=True, label='Processed', color='green')
plt.title('Distribution of Text Lengths')
plt.xlabel('Text Length')
plt.ylabel('Frequency')
plt.legend()
plt.tight_layout()
plt.show()
print(f"Average original text length: {df['original_text_length'].mean():.2f}")
```

```
print(f"Average processed text length: {df['processed_text_length'].mean():.2f}")

#Count unique words before and after
unique_words_original = set(' '.join(df['full_text']).split())
unique_words_processed = set(' '.join(df['full_text_processed']).split())

#Identify the most common words after preprocessing
processed_words_list = ' '.join(df['full_text_processed']).split()
most_common_processed_words = Counter(processed_words_list).most_common(10)


print(f"Unique words in original text: {len(unique_words_original)}")
print(f"Unique words in processed text: {len(unique_words_processed)}")

# most common words after preprocessing
print("\n🔥 Most common words after preprocessing:")
for word, count in most_common_processed_words:
    print(f"  {word}: {count}")
```

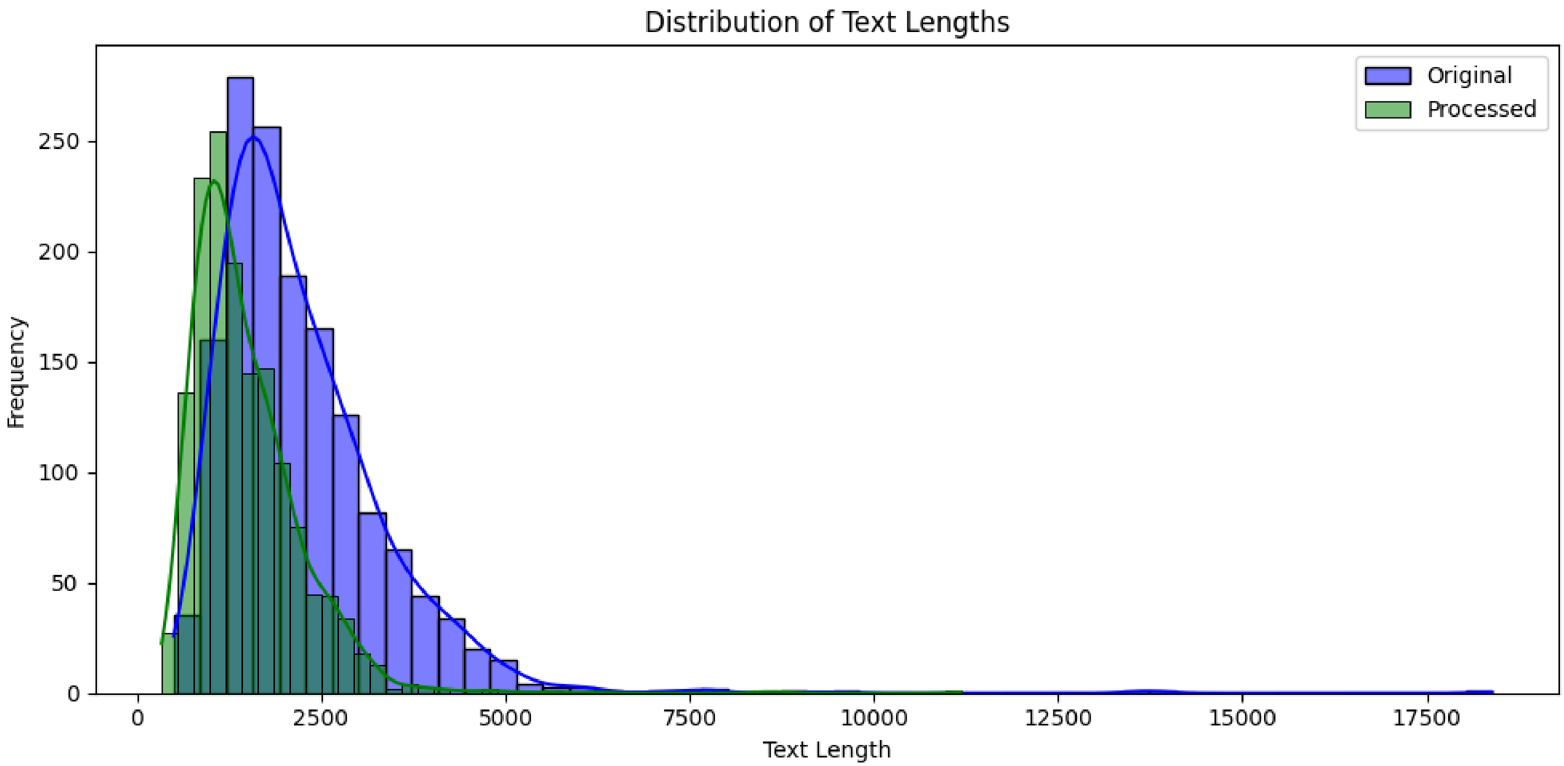
🧹 Preprocessing all articles...
✅ Preprocessing complete!

📝 BEFORE AND AFTER EXAMPLES
==

Example 1:
Original: worldcom ex-boss launches defence lawyers defending former worldcom chief bernie ebbers against a ba...
Processed: worldcom exboss launch defence lawyer defending former worldcom chief bernie ebbers battery fraud ch...

Example 2:
Original: german business confidence slides german business confidence fell in february knocking hopes of a sp...
Processed: german business confidence slide german business confidence fell february knocking hope speedy recov...

Example 3:
Original: bbc poll indicates economic gloom citizens in a majority of nations surveyed in a bbc world service ...
Processed: bbc poll indicates economic gloom citizen majority nation surveyed bbc world service poll believe wo...



Average original text length: 2233.46
Average processed text length: 1481.36
Unique words in original text: 35594
Unique words in processed text: 22486

🔥 Most common words after preprocessing:
  said: 4838
  year: 1872

```
would: 1711
also: 1426
new: 1334
people: 1323
```

📊 Feature Extraction and Statistical Analysis

🎯 Module 3: TF-IDF Analysis

Now we'll extract numerical features from our text using TF-IDF (Term Frequency-Inverse Document Frequency). This technique helps us identify the most important words in each document and across the entire corpus.

TF-IDF Key Concepts:

- **Term Frequency (TF):** How often a word appears in a document
- **Inverse Document Frequency (IDF):** How rare a word is across all documents
- **TF-IDF Score:** TF × IDF - balances frequency with uniqueness

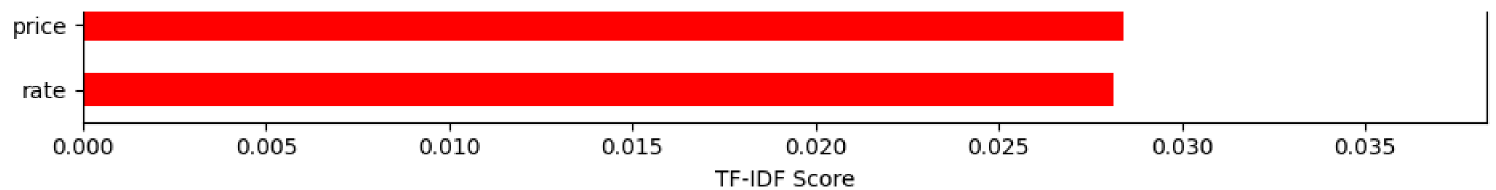
💡 **Business Value:** TF-IDF helps us identify the most distinctive and important terms for each news category.

```python
# Create TF-IDF vectorizer

tfidf_vectorizer = TfidfVectorizer(
    max_features=4500,  # Limit vocabulary for computational efficiency
    ngram_range=(1, 2), # Include unigrams and bigrams
    min_df=4,  # Ignore terms that appear in less than 2 documents
    max_df=0.2 # Ignore terms that appear in more than 8% of documents
)

# Fit and transform the processed text
print("🔢 Creating TF-IDF features...")
tfidf_matrix = tfidf_vectorizer.fit_transform(df['full_text_processed'])
feature_names = tfidf_vectorizer.get_feature_names_out()

print(f"✅ TF-IDF matrix created!")
print(f"📊 Shape: {tfidf_matrix.shape}")
print(f"📝 Vocabulary size: {len(feature_names)}")
print(f"🔢 Sparsity: {(1 - tfidf_matrix.nnz / (tfidf_matrix.shape[0] * tfidf_matrix.shape[1])) * 100:.2f}%")

# Convert to DataFrame for easier analysis
tfidf_df = pd.DataFrame(tfidf_matrix.toarray(), columns=feature_names)
tfidf_df['Category'] = df['Category'].values

print("\n🔍 Sample TF-IDF features:")
print(tfidf_df.iloc[:5, :15])  # Show first 5 rows and 15 features
```

```
🔢 Creating TF-IDF features...
✅ TF-IDF matrix created!
📊 Shape: (1490, 4500)
📝 Vocabulary size: 4500
🔢 Sparsity: 97.56%

🔍 Sample TF-IDF features:
   abc  ability     able  abroad  absence  absolute  absolutely  abuse  \
0  0.0      0.0  0.00000     0.0      0.0       0.0         0.0    0.0
1  0.0      0.0  0.00000     0.0      0.0       0.0         0.0    0.0
2  0.0      0.0  0.00000     0.0      0.0       0.0         0.0    0.0
3  0.0      0.0  0.02491     0.0      0.0       0.0         0.0    0.0
4  0.0      0.0  0.00000     0.0      0.0       0.0         0.0    0.0

   abused  academy  academy award  accept  acceptable  accepted  access
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
2     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
4     0.0      0.0            0.0     0.0         0.0       0.0     0.0
```

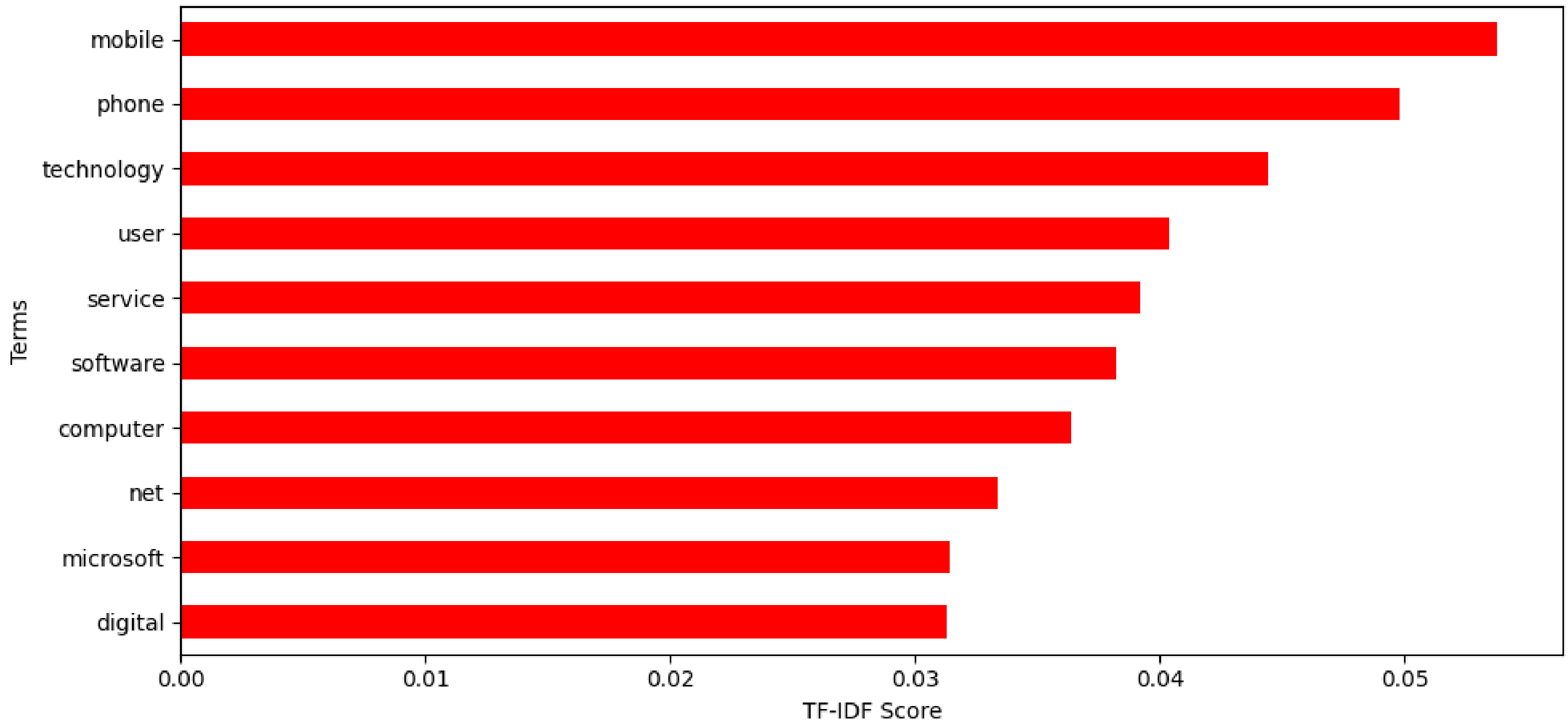
```
# Analyze most important terms per category
def get_top_tfidf_terms(category, n_terms=10):
    """
    Get top TF-IDF terms for a specific category


    """
    # 🚀 Implement category-specific TF-IDF analysis
    category_data = tfidf_df[tfidf_df['Category'] == category]

    # Calculate mean TF-IDF scores for this category
    mean_scores = category_data.drop('Category', axis=1).mean().sort_values(ascending=False)

    return mean_scores.head(n_terms)

# Analyze top terms for each category
print("🏷️ TOP TF-IDF TERMS BY CATEGORY")
print("=" * 50)

categories = df['Category'].unique()
category_terms = {}

for category in categories:
    top_terms = get_top_tfidf_terms(category, n_terms=10)
    category_terms[category] = top_terms

    print(f"\n📰 {category.upper()}:")
    for term, score in top_terms.items():
```

```
        print(f"  {term}: {score:.4f}")

#Visualize top terms
def plot_bar_chart(category, terms_scores):
    plt.figure(figsize=(10,5))
    terms_scores.sort_values().plot(kind='barh', color='red') #started with sky blue, but changed to red due to visual preferences
    plt.title(f'Top Terms for {category}')
    plt.xlabel('TF-IDF Score')
    plt.ylabel('Terms')
    plt.tight_layout()


#Word clouds for each category
print("\n🌎 WORD CLOUDS FOR EACH CATEGORY")
print("=" * 50)
def plot_worldcloud(category, terms_scores):
  wc = WordCloud(background_color='white', width=800, height=400)
  wc.generate_from_frequencies(terms_scores.to_dict())
  plt.figure(figsize=(10, 5))
  plt.imshow(wc, interpolation='bilinear')
  plt.axis('off')
  plt.title(f'Word Cloud for {category}')
  plt.tight_layout()


# Plotting the visualizations
for category, terms in category_terms.items():
    plot_bar_chart(category, terms)
    plt.show() # Show the bar chart
    plot_worldcloud(category, terms)
    plt.show() # Show the word cloud

# Heatmap
heatmap_df = pd.DataFrame(category_terms).fillna(0)
plt.figure(figsize=(15, 10))
sns.heatmap(heatmap_df.T, annot=True, cmap='YlOrRd', fmt='.3f')
plt.title('TF-IDF Scores by Category')
plt.xlabel('Category')
plt.ylabel('Terms')
plt.tight_layout()
```

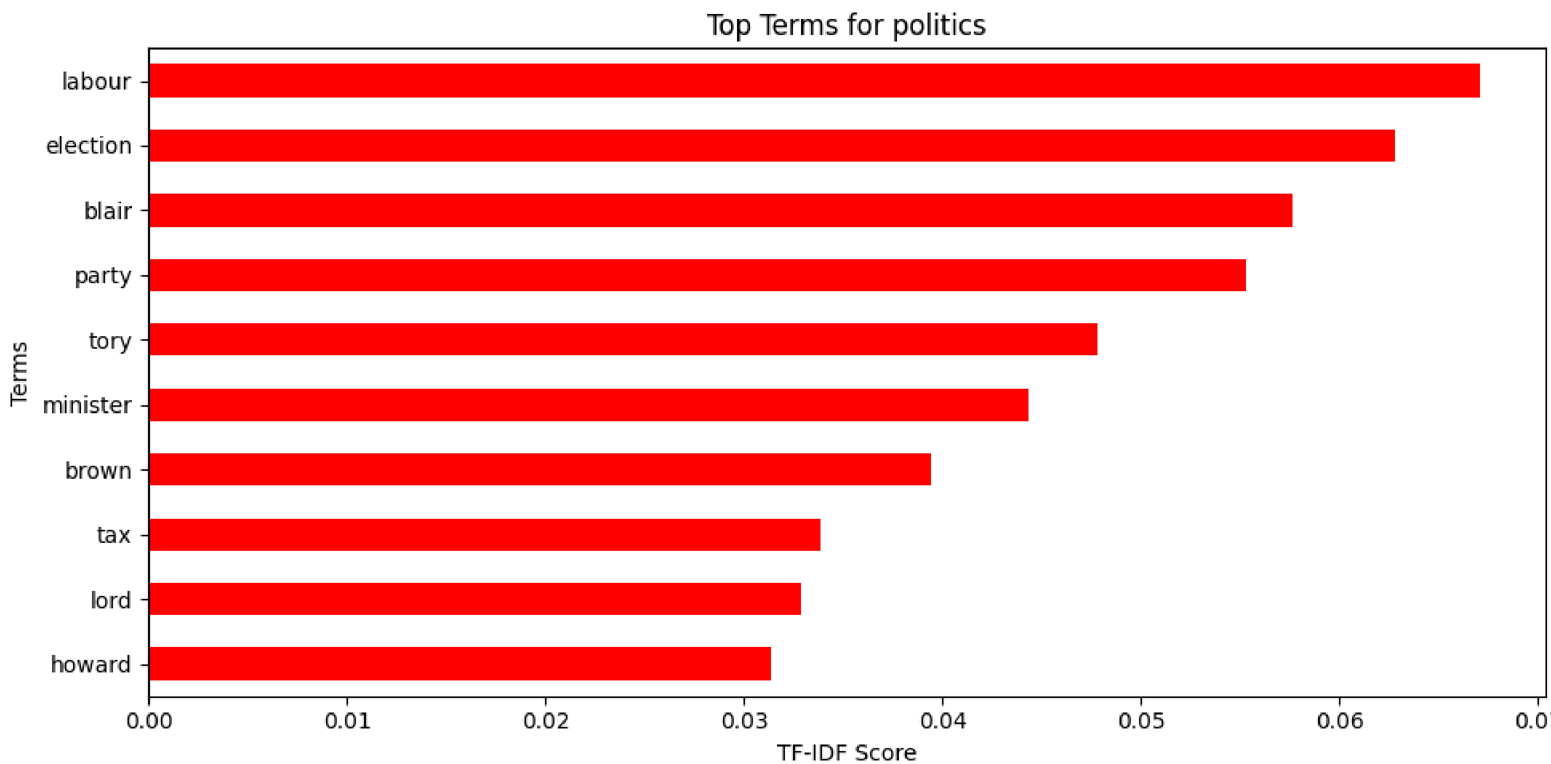


Word Cloud for business

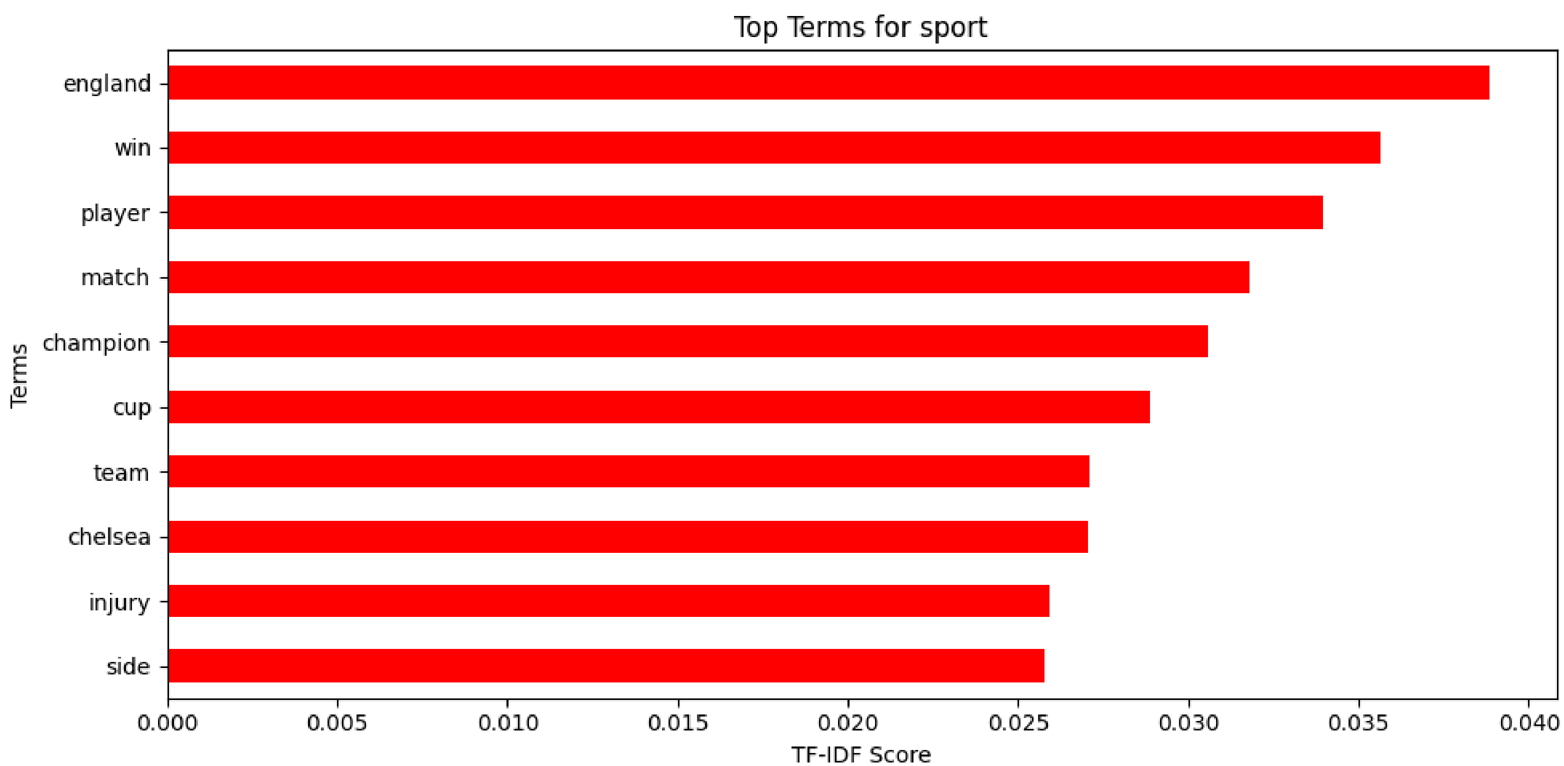
Top Terms for tech



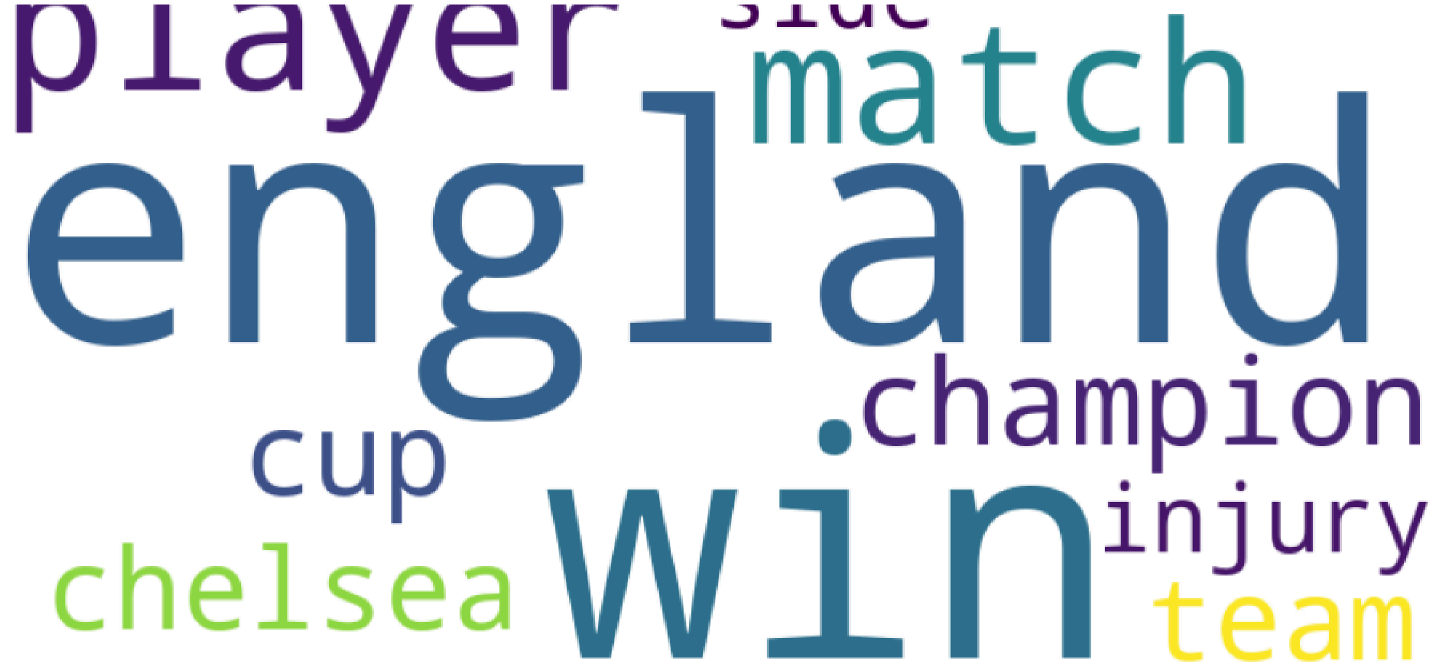
Word Cloud for tech



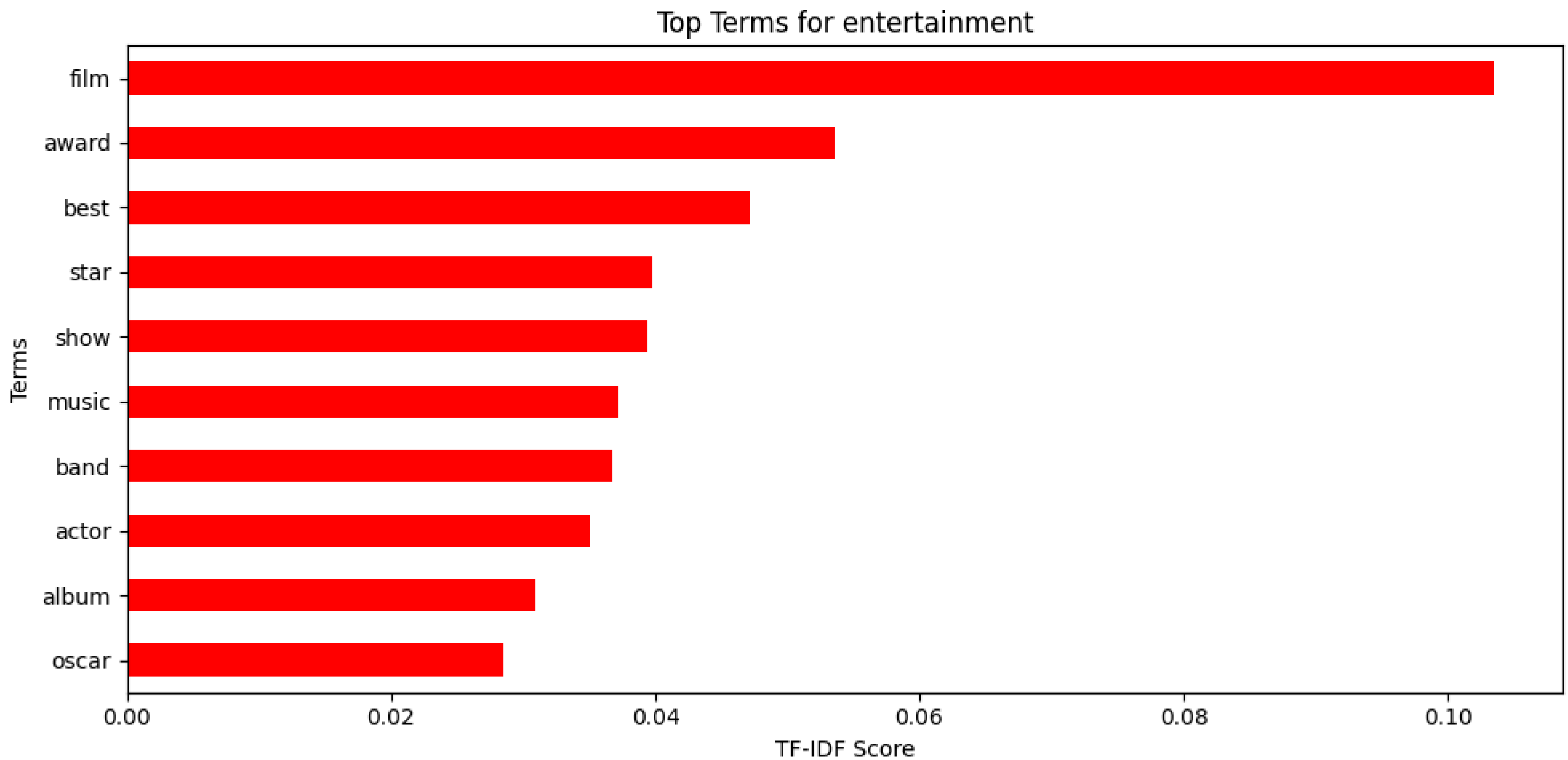
Word Cloud for politics



Word Cloud for sport



player
match
england
champion
cup
win
injury
chelsea
team



Top Terms for entertainment
film
award
best
star
show
music
band
actor
album
oscar
Terms
0.00
0.02
0.04
0.06
0.08
0.10
TF-IDF Score

🏷️ Part-of-Speech Analysis

🎯 Module 4: Grammatical Pattern Analysis

Let's analyze the grammatical patterns in different news categories using Part-of-Speech (POS) tagging. This can reveal interesting differences in writing styles between categories.

POS Analysis Applications:

- **Writing Style Detection:** Different categories may use different grammatical patterns
- **Content Quality Assessment:** Proper noun density, adjective usage, etc.
- **Feature Engineering:** POS tags can be features for classification

💡 **Hypothesis:** Sports articles might have more action verbs, while business articles might have more numbers and proper nouns.

```
def analyze_pos_patterns(text):
    """
    Analyze POS patterns in text

    """
    if not text or pd.isna(text):
        return {}

    # 🚀 Implement POS analysis
    # Tokenize and tag
    tokens = word_tokenize(str(text))
    pos_tags = pos_tag(tokens)

    # Count POS categories
    pos_counts = Counter([tag for word, tag in pos_tags])
    total_words = len(pos_tags)

    if total_words == 0:
        return {}

    # Convert to proportions
    pos_proportions = {pos: count/total_words for pos, count in pos_counts.items()}

    return pos_proportions

# Apply POS analysis to all articles
print("🏷️ Analyzing POS patterns...")

# Analyze POS for each article
pos_results = []
```

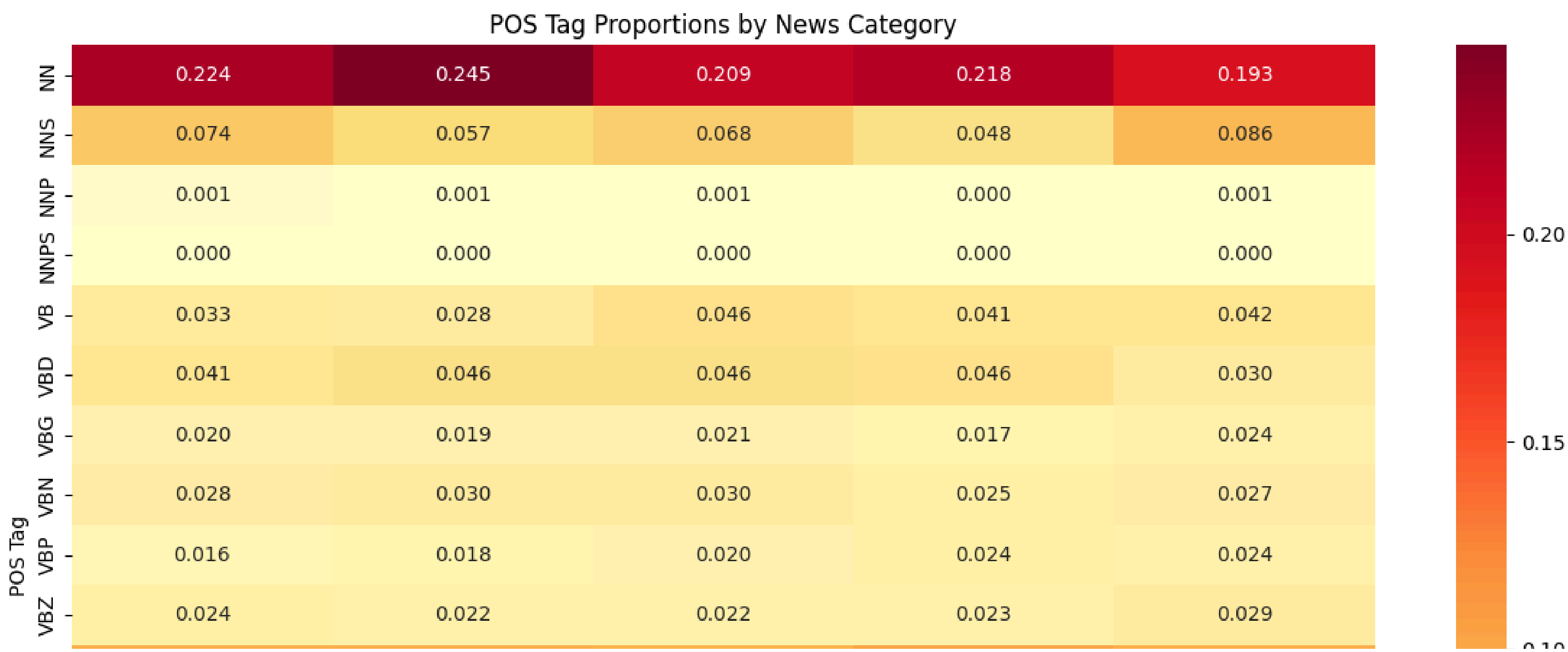
```
for idx, row in df.iterrows():
    pos_analysis = analyze_pos_patterns(text=row['Text'])
    pos_analysis['Category'] = row['Category']
    pos_analysis['Article_ID'] = row['ArticleId']
    pos_results.append(pos_analysis)

# Convert to DataFrame
pos_df = pd.DataFrame(pos_results).fillna(0)

print(f"✅ POS analysis complete!")
print(f"📊 Found {len(pos_df.columns)-2} different POS tags")

# Show sample results
print("\n📝 Sample POS analysis:")
print(pos_df.head())
```

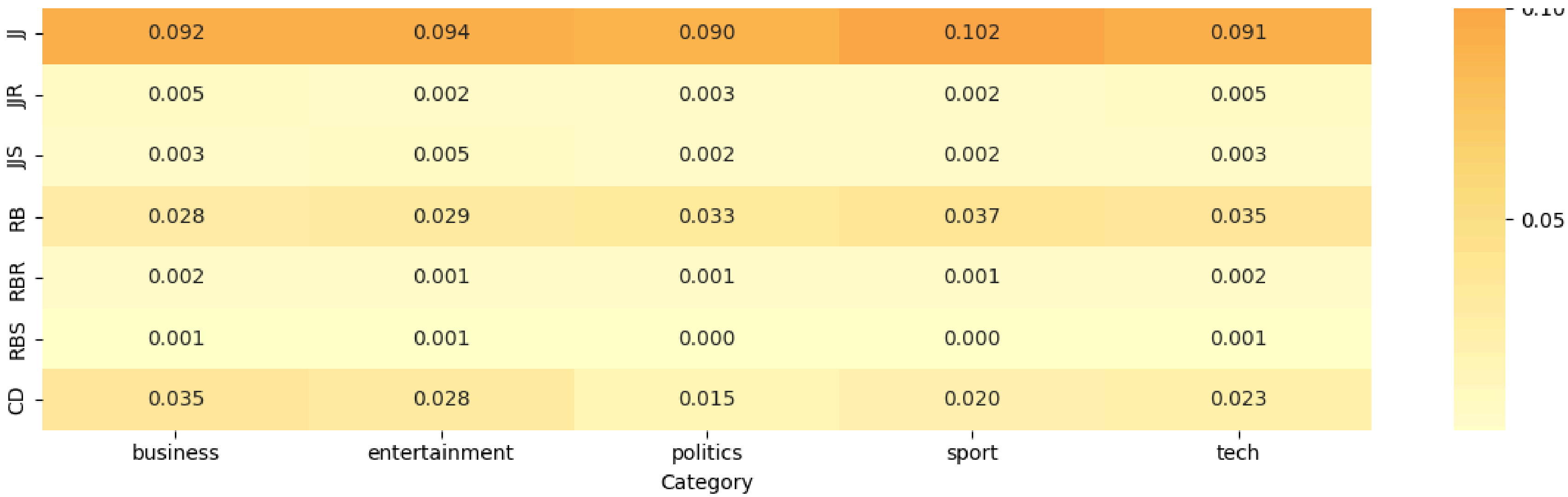
```
🏷️ Analyzing POS patterns...
✅ POS analysis complete!
📊 Found 43 different POS tags

📝 Sample POS analysis:
         JJ       NNS        NN       VBG        IN        DT       VBP  \
0  0.088608  0.113924  0.231013  0.025316  0.110759  0.066456  0.015823
1  0.119883  0.070175  0.233918  0.032164  0.134503  0.081871  0.014620
2  0.079044  0.079044  0.200368  0.025735  0.119485  0.095588  0.016544
3  0.083582  0.107463  0.156716  0.022388  0.122388  0.062687  0.041791
4  0.089005  0.078534  0.212042  0.028796  0.123037  0.102094  0.015707

        VBN      PRP$         .  ...   FW  SYM  WP$  NNP  NNPS  POS   UH    #  \
0  0.041139  0.012658  0.037975  ...  0.0  0.0  0.0  0.0   0.0  0.0  0.0  0.0
1  0.029240  0.005848  0.040936  ...  0.0  0.0  0.0  0.0   0.0  0.0  0.0  0.0
2  0.029412  0.016544  0.040441  ...  0.0  0.0  0.0  0.0   0.0  0.0  0.0  0.0
3  0.017910  0.013433  0.046269  ...  0.0  0.0  0.0  0.0   0.0  0.0  0.0  0.0
4  0.026178  0.015707  0.041885  ...  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
2  0.0  0.0
3  0.0  0.0
4  0.0  0.0

[5 rows x 45 columns]
```

```
# Analyze POS patterns by category
print("📊 POS PATTERNS BY CATEGORY")
print("=" * 50)

# Group by category and calculate mean proportions
pos_by_category = pos_df.groupby('Category').mean()
```

```
# Focus on major POS categories
major_pos = ['NN', 'NNS', 'NNP', 'NNPS', 'VB', 'VBD', 'VBG', 'VBN', 'VBP', 'VBZ',
             'JJ', 'JJR', 'JJS', 'RB', 'RBR', 'RBS', 'CD']

# Filter to only include major POS tags that exist in our data
available_pos = [pos for pos in major_pos if pos in pos_by_category.columns]

if available_pos:
    pos_summary = pos_by_category[available_pos]

    print("\n🎯 Key POS patterns by category:")
    print(pos_summary.round(4))

    # Create visualization
    plt.figure(figsize=(12, 8))
    sns.heatmap(pos_summary.T, annot=True, cmap='YlOrRd', fmt='.3f')
    plt.title('POS Tag Proportions by News Category')
    plt.xlabel('Category')
    plt.ylabel('POS Tag')
    plt.tight_layout()
    plt.show()


    print("\n💡 ANALYSIS QUESTIONS:")
    print("1. Which category has the highest proportion of proper nouns (NNP/NNPS)?: Business has the highest proportiom of proper nouns")
    print("2. Which category uses the most action verbs (VB, VBD, VBG)?: Politics had the most action verbs.")
    print("3. Are there interesting patterns in adjective (JJ) usage?: Yes, sports has the highest which is not surprising.")
    print("4. How does number (CD) usage vary across categories?: Numbers in business are used in every aspect of the category.")
    print("From stocks, market forecasts, earning reports and more. This is most likely why it dominates in frequency.")
    print("I was surprised to see that entertainment was the second highest. I assume with would have to be related to seasons and episodes.")
    print("The one with the least frequency was Politics. I thought it would not be last due to poll numbers being such a large part of the community.")
else:
    print("⚠️ No major POS tags found in the analysis. Check your POS tagging implementation.")
```

```
tech           0.1932  0.0855  0.0006  0.0000  0.0420  0.0299  0.0236  0.0270

                  VBP     VBZ      JJ     JJR     JJS      RB     RBR     RBS  \
Category
business       0.0158  0.0241  0.0920  0.0045  0.0033  0.0276  0.0018  0.0006
entertainment  0.0179  0.0223  0.0939  0.0024  0.0050  0.0286  0.0010  0.0010
politics       0.0199  0.0224  0.0901  0.0032  0.0017  0.0325  0.0014  0.0003
sport          0.0244  0.0233  0.1015  0.0019  0.0018  0.0373  0.0012  0.0003
tech           0.0235  0.0285  0.0913  0.0052  0.0025  0.0346  0.0022  0.0007

                   CD
Category
business       0.0347
entertainment  0.0278
politics       0.0147
sport          0.0203
tech           0.0228
```





💡 ANALYSIS QUESTIONS:
1. Which category has the highest proportion of proper nouns (NNP/NNPS)?: Business has the highest proportiom of proper nouns
2. Which category uses the most action verbs (VB, VBD, VBG)?: Politics had the most action verbs.
3. Are there interesting patterns in adjective (JJ) usage?: Yes, sports has the highest which is not surprising.
4. How does number (CD) usage vary across categories?: Numbers in business are used in every aspect of the category.
From stocks, market forecasts, earning reports and more. This is most likely why it dominates in frequency.

🌳 Syntax Parsing and Semantic Analysis

🎯 Module 5: Understanding Sentence Structure

Now we'll use spaCy to perform dependency parsing and extract semantic relationships from our news articles. This helps us understand not just what words are present, but how they relate to each other.

Dependency Parsing Applications:

- **Relationship Extraction:** Find connections between entities
- **Event Detection:** Identify who did what to whom
- **Information Extraction:** Extract structured facts from unstructured text

💡 **Business Value:** Understanding sentence structure helps extract more precise information about events, relationships, and actions mentioned in news articles.

```
def extract_syntactic_features(text):
    """
    Extract syntactic features using spaCy dependency parsing

    """
    if not text or pd.isna(text):
        return {}

    # Process text with spaCy
    doc = nlp(str(text))

    features = {
        'num_sentences': len(list(doc.sents)),
        'num_tokens': len(doc),
        'dependency_relations': [],
        'noun_phrases': [],
        'verb_phrases': [],
        'subjects': [],
        'objects': []
    }

    # 🚀 Extract syntactic features

    # Extract dependency relations
    for token in doc:
        if not token.is_space and not token.is_punct:
            features['dependency_relations'].append(token.dep_)

    # Extract noun phrases
```

```
    # Extract noun phrases
    for chunk in doc.noun_chunks:
        features['noun_phrases'].append(chunk.text.lower())

    # Extract verb phrases
    for chunk in doc.noun_chunks:
            features['verb_phrases'].append(chunk.text.lower())

    # Extract subjects and objects
    for token in doc:
        if token.dep_ in ['nsubj', 'nsubjpass']:  # Subjects
            features['subjects'].append(token.text.lower())
        elif token.dep_ in ['dobj', 'iobj', 'pobj']:  # Objects
            features['objects'].append(token.text.lower())

    # Count dependency types
    dep_counts = Counter(features['dependency_relations'])
    features['dependency_counts'] = dict(dep_counts)

    return features

# Apply syntactic analysis to sample articles
print("🌳 Performing syntactic analysis...")

# Analyze first few articles
syntactic_results = []
for idx, row in df.head(5).iterrows():
    features = extract_syntactic_features(row['full_text'])
    features['Category'] = row['Category']
    features['Article_Id'] = row['ArticleId']
    syntactic_results.append(features)

print("✅ Syntactic analysis complete!")

# Display results
for i, result in enumerate(syntactic_results):
    print(f"\n📰 Article {i+1} ({result['Category']}):")
    print(f"  Sentences: {result['num_sentences']}")
    print(f"  Tokens: {result['num_tokens']}")
    print(f"  Noun phrases: {result['noun_phrases'][:20]}...")  # Show first 20
    print(f"  Verb phrases: {result['verb_phrases'][:20]}...") # Show first 20
    print(f"  Subjects: {result['subjects'][:20]}...")  # Show first 20
    print(f"  Objects: {result['objects'][:20]}...")  # Show first 20
```

```
🌳 Performing syntactic analysis...
✅ Syntactic analysis complete!

📰 Article 1 (business):
  Sentences: 15
```

```
Tokens: 346
Noun phrases: ['-', 'boss', 'defence lawyers', 'former worldcom chief bernie ebbers', 'a battery', 'fraud charges', 'a company', 'their first witness
Verb phrases: ['-', 'boss', 'defence lawyers', 'former worldcom chief bernie ebbers', 'a battery', 'fraud charges', 'a company', 'their first witness
Subjects: ['-', 'boss', 'worldcom', 's', 'warnings', 'ebbers', 'lawyers', 'ebbers', 'cooper', 'who', 'andersen', 'she', 'andersen', 'lawyers', 'he',
Objects: ['lawyers', 'ebbers', 'battery', 'charges', 'company', 'witness', 'accounting', 'directors', 'practices', 'giant', '2002', 'collapse', 'firm

📰 Article 2 (business):
 Sentences: 15
 Tokens: 368
 Noun phrases: ['german business confidence', 'german business confidence', 'february', 'hopes', 'a speedy recovery', 'europe s largest economy', 'mur
 Verb phrases: ['german business confidence', 'german business confidence', 'february', 'hopes', 'a speedy recovery', 'europe s largest economy', 'mur
 Subjects: ['confidence', 'ifo', 'index', 'study', 'outlook', 'observers', 'sector', 'activity', 'we', 'index', 'knock', 'reason', 'economy', 'economy
 Objects: ['confidence', 'february', 'hopes', 'recovery', 'economy', '95.5', 'february', '97.5', 'january', 'decline', 'months', 'sectors', 'weidenste

📰 Article 3 (business):
 Sentences: 24
 Tokens: 587
 Noun phrases: ['bbc poll', 'economic gloom citizens', 'a majority', 'nations', 'a bbc world service poll', 'the world economy', 'most respondents', '
 Verb phrases: ['bbc poll', 'economic gloom citizens', 'a majority', 'nations', 'a bbc world service poll', 'the world economy', 'most respondents', '
 Subjects: ['poll', 'citizens', 'economy', 'respondents', 'economy', 'majority', 'they', 'people', 'which', 'poll', 'majority', 'economy', 'who', 'it'
 Objects: ['majority', 'nations', 'poll', 'outlook', 'countries', 'future', 'countries', 'poll', 'disaster', 'people', 'countries', 'respondents', 'cc

📰 Article 4 (tech):
 Sentences: 31
 Tokens: 724
 Noun phrases: ['lifestyle', 'mobile choice', 'faster  better or funkier hardware', 'phone firms', 'more handsets  research', 'instead  phone firms',
 Verb phrases: ['lifestyle', 'mobile choice', 'faster  better or funkier hardware', 'phone firms', 'more handsets  research', 'instead  phone firms',
 Subjects: ['lifestyle', 'governs', 'firms', 'firms', 'consumers', 'handsets', 'they', 'chip', 'michael', 'we', 'technologies', 'he', 'we', 'them', 'i
 Objects: ['choice', 'hardware', 'research', 'more', 'customers', 'technology', 'sake', 'lifestyle', 'size', 'memory', 'depth', 'study', 'ericsson', '

📰 Article 5 (business):
 Sentences: 17
 Tokens: 417
 Noun phrases: ['enron bosses', 'former enron directors', 'a $168m', '£89m) settlement deal', 'a shareholder lawsuit', 'the collapse', 'the energy fir
 Verb phrases: ['enron bosses', 'former enron directors', 'a $168m', '£89m) settlement deal', 'a shareholder lawsuit', 'the collapse', 'the energy fir
 Subjects: ['bosses', 'directors', 'plaintiff', 'news', '10', 'settlement', 'enron', 'it', 'it', 'firm', 'demise', 'settlement', 'lerach', 'this', 'he
 Objects: ['168', 'm', 'lawsuit', 'collapse', 'firm', 'california', 'directors', 'm', 'pockets', 'courts', 'approval', '2001', 'millions', 'dollars',
```

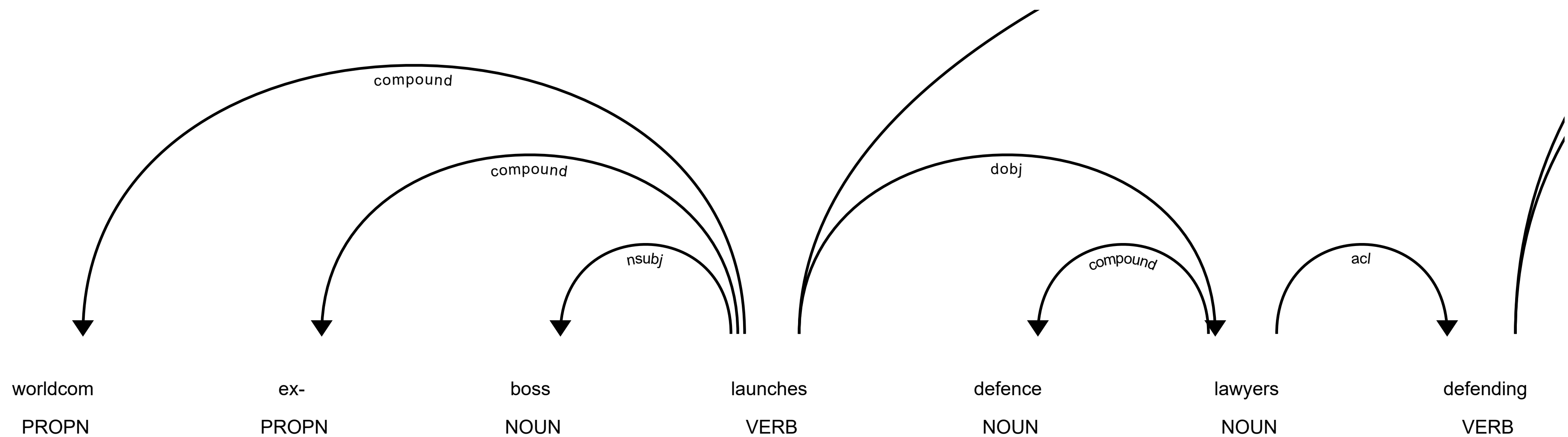
```python
# Visualize dependency parsing for a sample sentence
from spacy import displacy

# Choose a sample sentence
sample_sentence = df.iloc[0]['full_text']
print(f"📝 Sample sentence: {sample_sentence}")

# Process with spaCy
doc = nlp(sample_sentence)

# Display dependency tree (this works best in Jupyter)
print("\n🌳 Dependency Parse Visualization:")
```

```
try:
    # This will create an interactive visualization in Jupyter
    displacy.render(doc, style="dep", jupyter=True)
except:
    # Fallback: print dependency information
    print("\n🔗 Dependency Relations:")
    for token in doc:
        if not token.is_space and not token.is_punct:
            print(f"  {token.text} --> {token.dep_} --> {token.head.text}")

# Compare syntactic complexity
print("\n📊 Syntactic Complexity by Category:")
complexity_stats = defaultdict(lambda: defaultdict(list))
for idx, row in df.head().iterrows():
    features = extract_syntactic_features(row['full_text'])
    complexity_stats[row['Category']]['Sentence_Count'].append(features['num_sentences'])
    complexity_stats[row['Category']]['Token_Count'].append(features['num_tokens'])
    complexity_stats[row['Category']]['Noun_Count'].append(len(features['noun_phrases']))
    complexity_stats[row['Category']]['Subject_Count'].append(len(features['subjects']))
    complexity_stats[row['Category']]['Object_Count'].append(len(features['objects']))

complexity_df = pd.DataFrame(complexity_stats).T

# Calculate the mean of the lists in each cell
complexity_df_mean = complexity_df.applymap(lambda x: np.mean(x) if isinstance(x, list) else x)

print(complexity_df_mean.round(2))

#visualize syntatic complexity
plt.figure(figsize=(12, 8))
sns.barplot(data=complexity_df_mean.melt(ignore_index=False).reset_index(),
            x='index', y='value', hue='variable')
plt.title('Syntactic Complexity by Category')
plt.xlabel('Category')
plt.ylabel('Count')
plt.legend(title='Feature')
plt.tight_layout()
plt.show()

#extract action patterns
def extract_svo_patterns(text):
  doc = nlp(text)
  svo_triples = []
  for sent in doc.sent: #this will be to look for main verbs
      for tokenm in sent:
        if token.pos_ == 'VERB' and token.dep_ == "ROOT":
          subject = [w for w in token.lefts if w.dep_ in ("nsubj", "nsubjpass")]
          object = [w for w in token.rights if w.dep_ in ("dobj", "iobj", "pobj")]
```

```
          if subject and object:
            svo_triples.append((subject[0].text, token.text, object[0].text))
  return svo_triples
def plot_svo_graph(svo_triples):
    G = nx.Digraph()
    for triple in svo_triples:
        G.add_edge(triple[0], triple[1])
        G.add_edge(triple[1], triple[2])
    pos = nx.spring_layout(G)
    plt.figure(figsize=(12, 8))
    nx.draw(G, pos, with_labels=True, node_size=2000, node_color='skyblue', font_size=10, font_color='black', arrows=True)
    plt.title("Action Patterns")
    plt.show()

#identify most common dependency relations per category:
from collections import Counter

def count_deps_in_doc(text):
    doc = nlp(text)
    return Counter([tok.dep_ for tok in doc if not tok.is_punct and not tok.is_space])

# Build a list of dicts: one per document
records = []
for idx, row in df.iterrows():
    dep_counts = count_deps_in_doc(row['full_text'])
    dep_counts['Category'] = row['Category']
    records.append(dep_counts)

# Create a DataFrame where each column is a dep label and rows are docs
dep_df = pd.DataFrame(records).fillna(0)

# Group by category, summing all dependency counts
agg_by_cat = dep_df.groupby('Category').sum()

# Drop the non-dependency column if present
agg_by_cat = agg_by_cat.drop(columns=['Category'], errors='ignore')

top_n = 5
top_deps_per_cat = {
    cat: df_row.nlargest(top_n).index.tolist()
    for cat, df_row in agg_by_cat.iterrows()
}

print("Top 10 dependency relations by category:")
for cat, deps in top_deps_per_cat.items():
    print(f"  • {cat}: {', '.join(deps)}")

#Visualize the common dependency
```

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

# Melt for plotting
melted = agg_by_cat.reset_index().melt(
    id_vars='Category',
    var_name='DepRel',
    value_name='Count'
)

# Keep only the top M relations overall
top_global = (
    melted.groupby('DepRel')['Count']
          .sum()
          .nlargest(10)
          .index
)
plot_df = melted[melted['DepRel'].isin(top_global)]

plt.figure(figsize=(10, 6))
sns.barplot(data=plot_df, x='DepRel', y='Count', hue='Category')
plt.xticks(rotation=45)
plt.title("Top 10 Dependency Relations Across Categories")
plt.tight_layout()
plt.show()

import numpy as np
from collections import Counter

#Create features for classification based on syntax
def extract_syntax_features(text, nlp):
    """
    Returns a dict of syntactic features for a single document.
    """
    doc = nlp(text)
    feats = {}

    # Part-of-Speech Counts
    pos_counts = Counter(tok.pos_ for tok in doc if not tok.is_punct and not tok.is_space)
    for pos in ['NOUN', 'VERB', 'ADJ', 'ADV', 'PRON', 'PROPN']:
        feats[f'POS_{pos}'] = pos_counts.get(pos, 0)

    # Dependency Relation Counts
    dep_counts = Counter(tok.dep_ for tok in doc if not tok.is_punct and not tok.is_space)
    for dep in ['nsubj', 'dobj', 'amod', 'ROOT', 'prep', 'pobj', 'advmod']:
        feats[f'DEP_{dep}'] = dep_counts.get(dep, 0)

    # Dependency Tree Depth (per sentence)
```

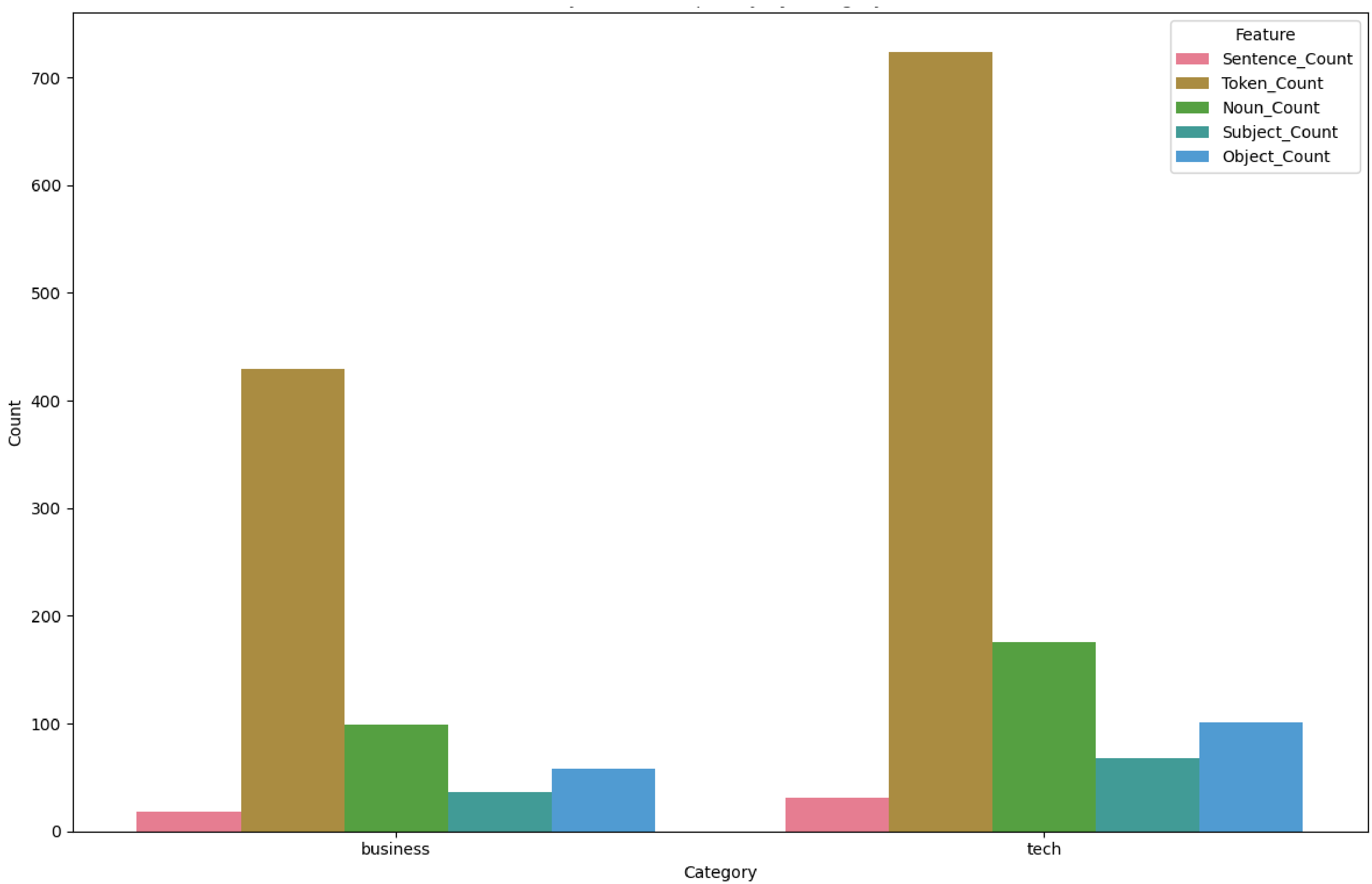
```
def depth(token):
    if not list(token.children):
        return 1
    return 1 + max(depth(child) for child in token.children)

depths = [depth(sent.root) for sent in doc.sents]
feats['max_tree_depth'] = max(depths) if depths else 0
feats['avg_tree_depth'] = np.mean(depths) if depths else 0

# Average Dependency Distance
dists = [abs(tok.i - tok.head.i) for tok in doc if tok.head != tok]
feats['mean_dep_distance'] = np.mean(dists) if dists else 0

#  SVO Pattern Count
svo_triples = []
for sent in doc.sents:
    for tok in sent:
        if tok.pos_ == 'VERB' and tok.dep_ == 'ROOT':
            subj = [w for w in tok.lefts if w.dep_ in ('nsubj','nsubjpass')]
            obj  = [w for w in tok.rights if w.dep_ in ('dobj','iobj','pobj')]
            if subj and obj:
                svo_triples.append((subj[0].text, tok.text, obj[0].text))
feats['num_svo'] = len(svo_triples)

# Sentence Count
feats['num_sentences'] = len(list(doc.sents))

return feats
```



📊 Syntactic Complexity by Category:

	Sentence_Count	Token_Count	Noun_Count	Subject_Count	Object_Count
business	17.75	429.5	98.5	36.5	58.0
tech	31.00	724.0	176.0	68.0	101.0

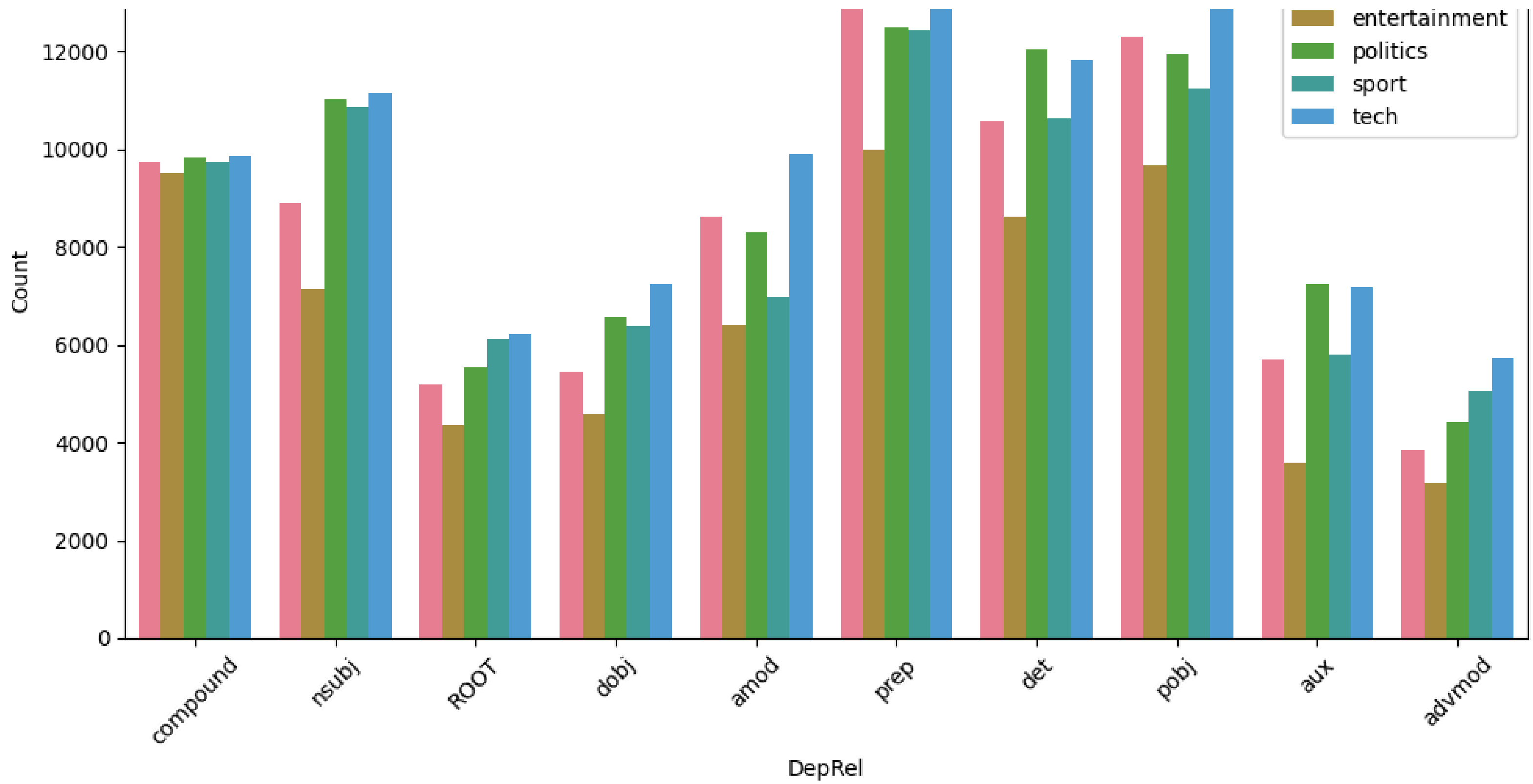
Syntactic Complexity by Category



Top 10 dependency relations by category:

- business: prep, pobj, det, compound, nsubj
- entertainment: prep, pobj, compound, det, nsubj
- politics: prep, det, pobj, nsubj, compound
- sport: prep, pobj, nsubj, det, compound
- tech: prep, pobj, det, nsubj, amod

Top 10 Dependency Relations Across Categories



entertainment
politics
sport
tech
Count
0
2000
4000
6000
8000
10000
12000
compound
nsubj
ROOT
dobj
amod
prep
det
pobj
aux
advmod
DepRel

😊 Sentiment and Emotion Analysis

🎯 Module 6: Understanding Emotional Tone

Let's analyze the sentiment and emotional tone of our news articles. This can reveal interesting patterns about how different types of news are presented and perceived.

Sentiment Analysis Applications:

- **Media Bias Detection:** Identify emotional slant in news coverage
- **Public Opinion Tracking:** Monitor sentiment trends over time
- **Content Recommendation:** Suggest articles based on emotional tone

💡 **Hypothesis:** Different news categories might have different emotional profiles - sports might be more positive, politics more negative, etc.

```
# Initialize sentiment analyzer
sia = SentimentIntensityAnalyzer()

def analyze_sentiment(text):
    """
    Analyze sentiment using VADER sentiment analyzer

    """
    if not text or pd.isna(text):
        return {'compound': 0, 'pos': 0, 'neu': 1, 'neg': 0}

    # 🚀  Implement sentiment analysis
    scores = sia.polarity_scores(str(text))

    # Add interpretation
    if scores['compound'] >= 0.05:
        scores['sentiment_label'] = 'positive'
    elif scores['compound'] <= -0.05:
        scores['sentiment_label'] = 'negative'
    else:
        scores['sentiment_label'] = 'neutral'

    return scores

# Apply sentiment analysis to all articles
print("😊 Analyzing sentiment...")

sentiment_results = []
for idx, row in df.iterrows():
    # Analyze the full text column
```

```
    full_sentiment = analyze_sentiment(row['full_text'])

    result = {
        'article_id': row['ArticleId'],
        'category': row['Category'],
        'full_sentiment': full_sentiment['compound'],
        'full_label': full_sentiment['sentiment_label'],
        'pos_score': full_sentiment['pos'],
        'neu_score': full_sentiment['neu'],
        'neg_score': full_sentiment['neg']
    }
    sentiment_results.append(result)

# Convert to DataFrame
sentiment_df = pd.DataFrame(sentiment_results)

print("✅ Sentiment analysis complete!")
print(f"📊 Analyzed {len(sentiment_df)} articles")

# Display sample results
print("\n📝 Sample sentiment results:")
print(sentiment_df[['category', 'full_sentiment', 'full_label']].head())
```

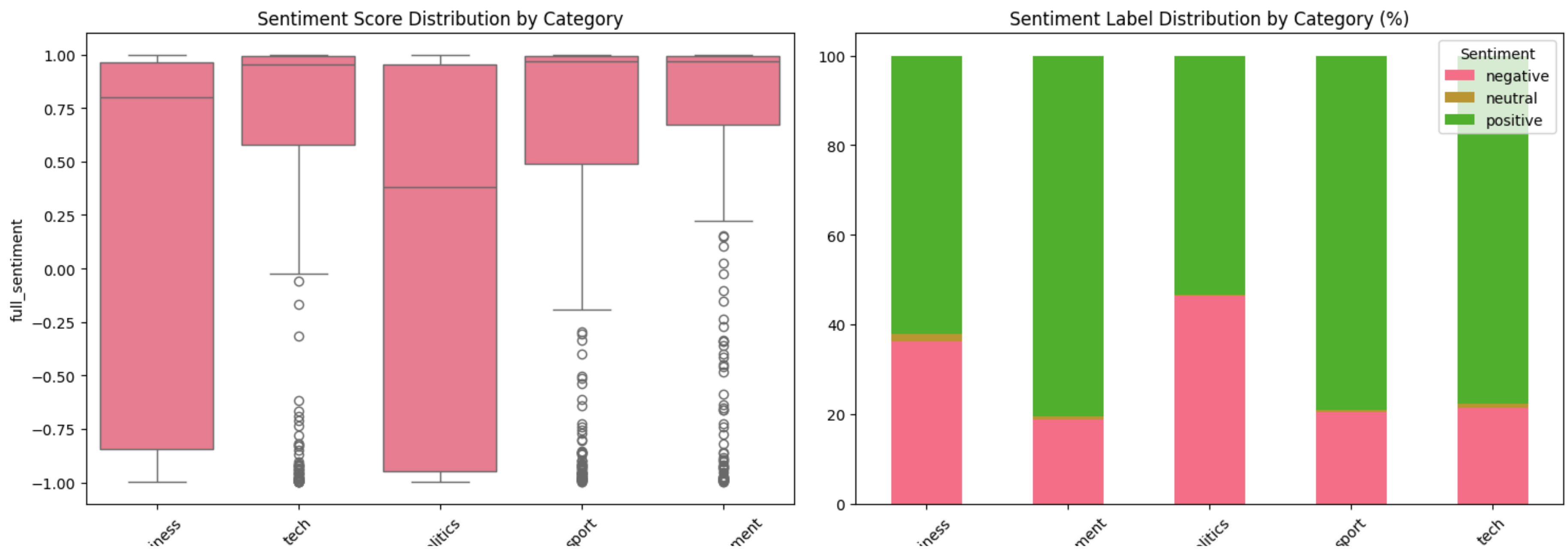
```
😊 Analyzing sentiment...
✅ Sentiment analysis complete!
📊 Analyzed 1490 articles

📝 Sample sentiment results:
   category  full_sentiment full_label
0  business         -0.9701   negative
1  business          0.7623   positive
2  business         -0.9318   negative
3      tech          0.9554   positive
4  business         -0.9486   negative
```

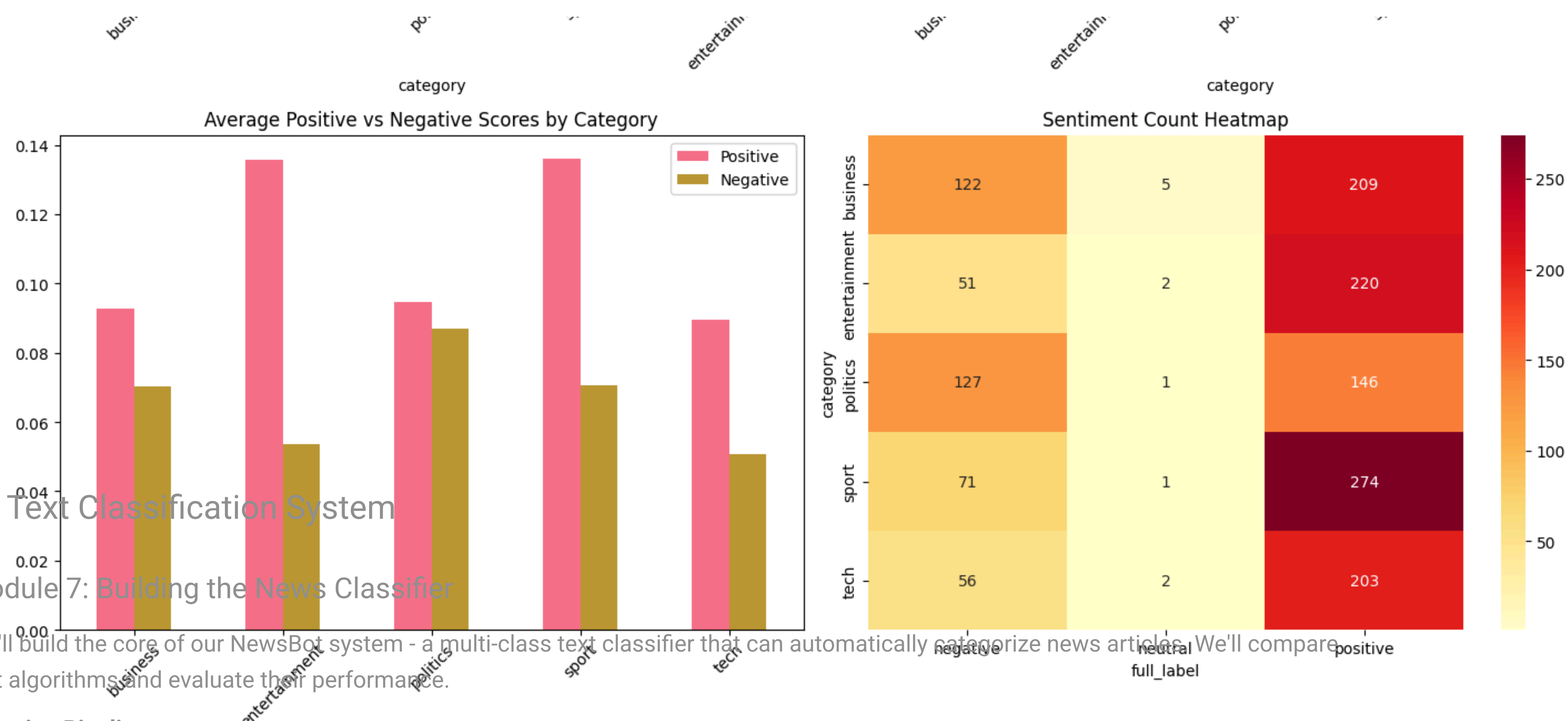
```
# Analyze sentiment patterns by category
print("📊 SENTIMENT ANALYSIS BY CATEGORY")
print("=" * 50)

from nltk.sentiment.vader import SentimentIntensityAnalyzer


#initialize
vader = SentimentIntensityAnalyzer()


import pandas as pd

# Calculate sentiment statistics by category
```

```
sentiment_by_category = sentiment_df.groupby('category').agg({
    'full_sentiment': ['mean', 'std', 'min', 'max'],
    'pos_score': 'mean',
    'neu_score': 'mean',
    'neg_score': 'mean'
}).round(4)

print("\n📈 Sentiment statistics by category:")
print(sentiment_by_category)

# Sentiment distribution by category
sentiment_dist = sentiment_df.groupby(['category', 'full_label']).size().unstack(fill_value=0)
sentiment_dist_pct = sentiment_dist.div(sentiment_dist.sum(axis=1), axis=0) * 100

print("\n📊 Sentiment distribution (%) by category:")
print(sentiment_dist_pct.round(2))

# Create visualizations
fig, axes = plt.subplots(2, 2, figsize=(15, 12))

# 1. Sentiment scores by category
sns.boxplot(data=sentiment_df, x='category', y='full_sentiment', ax=axes[0,0])
axes[0,0].set_title('Sentiment Score Distribution by Category')
axes[0,0].tick_params(axis='x', rotation=45)

# 2. Sentiment label distribution
sentiment_dist_pct.plot(kind='bar', ax=axes[0,1], stacked=True)
axes[0,1].set_title('Sentiment Label Distribution by Category (%)')
axes[0,1].tick_params(axis='x', rotation=45)
axes[0,1].legend(title='Sentiment')

# 3. Positive vs Negative scores
category_means = sentiment_df.groupby('category')[['pos_score', 'neg_score']].mean()
category_means.plot(kind='bar', ax=axes[1,0])
axes[1,0].set_title('Average Positive vs Negative Scores by Category')
axes[1,0].tick_params(axis='x', rotation=45)
axes[1,0].legend(['Positive', 'Negative'])

# 4. Sentiment vs Category heatmap
sentiment_pivot = sentiment_df.pivot_table(values='full_sentiment', index='category',
                                         columns='full_label', aggfunc='count', fill_value=0)
sns.heatmap(sentiment_pivot, annot=True, fmt='d', ax=axes[1,1], cmap='YlOrRd')
axes[1,1].set_title('Sentiment Count Heatmap')

plt.tight_layout()
plt.show()

# 💡 STUDENT TASK: Analyze sentiment patterns
```

```
print("Which categories are most positive/negative?: The most positive categories are entertainment and tech! The most negative categories are politics anc
print("Are there differences between title and content sentiment?: There is no title or content column in the dataset, so this analysis cannot be performec
print("How does sentiment vary within categories?: Politics ended up being even for the most part, with positive sentiment being at 46.35 and negative beir
print("Can sentiment be used as a feature for classification?: Due to the powerful semantic signals, yes it can be used as a feature for classification. It
```

```
tech                 0.5233  0.7557 -0.9991  0.9993    0.0895    0.8598

              neg_score
                   mean
category
business         0.0704
entertainment    0.0537
politics         0.0869
sport            0.0707
tech             0.0507

📊 Sentiment distribution (%) by category:
full_label     negative  neutral  positive
category
business          36.31     1.49     62.20
entertainment     18.68     0.73     80.59
politics          46.35     0.36     53.28
sport             20.52     0.29     79.19
tech              21.46     0.77     77.78
```





🏷️ Text Classification System

🎯 Module 7: Building the News Classifier

Now we'll build the core of our NewsBot system - a multi-class text classifier that can automatically categorize news articles. We'll compare different algorithms and evaluate their performance.

Classification Pipeline:

1. **Feature Engineering:** Combine TF-IDF with other features
2. **Model Training:** Train multiple algorithms
3. **Model Evaluation:** Compare performance metrics
4. **Model Selection:** Choose the best performing model

💡 **Business Impact:** Accurate classification enables automatic content routing, personalized recommendations, and efficient content management.

```
# Prepare features for classification
print("🔧 Preparing features for classification...")

# Create feature matrix
X_tfidf = tfidf_matrix.toarray()  # TF-IDF features

# Add sentiment features
sentiment_features = sentiment_df[['full_sentiment', 'pos_score', 'neu_score', 'neg_score']].values

# Add text length features
length_features = np.array([
```

```
    df['full_text'].str.len(),  # Character length
    df['full_text'].str.split().str.len(),  # Word count

]).T

# 🚀 Combine all features
X_combined = np.hstack([
    X_tfidf,
    sentiment_features,
    length_features
])

# Target variable
y = df['Category'].values

print(f"✅ Feature matrix prepared!")
print(f"📊 Feature matrix shape: {X_combined.shape}")
print(f"🎯 Number of classes: {len(np.unique(y))}")
print(f"📋 Classes: {np.unique(y)}")

# Split data into train and test sets
X_train, X_test, y_train, y_test = train_test_split(
    X_combined, y, test_size=0.2, random_state=42, stratify=y
)

print(f"\n📈 Data split:")
print(f"  Training set: {X_train.shape[0]} samples")
print(f"  Test set: {X_test.shape[0]} samples")
```

```
🔧 Preparing features for classification...
✅ Feature matrix prepared!
📊 Feature matrix shape: (1490, 4506)
🎯 Number of classes: 5
📋 Classes: ['business' 'entertainment' 'politics' 'sport' 'tech']

📈 Data split:
  Training set: 1192 samples
  Test set: 298 samples
```

```
# Train and evaluate multiple classifiers
print("🤖 Training multiple classifiers...")

# Define classifiers to compare
classifiers = {
    'Naive Bayes': MultinomialNB(),
    'Logistic Regression': LogisticRegression(random_state=42, max_iter=1000),
    'SVM': SVC(random_state=42, probability=True)  # used probability for better analysis
}
```

```
# Split TF-IDF features separately for MultinomialNB
# Use the same split parameters as the combined data split
X_train_tfidf, X_test_tfidf, _, _ = train_test_split(
    X_tfidf, y, test_size=0.2, random_state=42, stratify=y
)


# Train and evaluate each classifier
results = {}
trained_models = {}

for name, classifier in classifiers.items():
    print(f"\n🔄 Training {name}...")

    # 🚀 Train and evaluate classifier
    if name == 'Naive Bayes':
        # Train Naive Bayes only on non-negative TF-IDF features
        classifier.fit(X_train_tfidf, y_train)
        y_pred = classifier.predict(X_test_tfidf)
        y_pred_proba = classifier.predict_proba(X_test_tfidf) if hasattr(classifier, 'predict_proba') else None
        # Calculate CV scores on TF-IDF features
        cv_scores = cross_val_score(classifier, X_train_tfidf, y_train, cv=3, scoring='accuracy')
    else:
        # Train Logistic Regression and SVM on the combined features
        classifier.fit(X_train, y_train)
        y_pred = classifier.predict(X_test)
        y_pred_proba = classifier.predict_proba(X_test) if hasattr(classifier, 'predict_proba') else None
        # Calculate CV scores on combined features
        cv_scores = cross_val_score(classifier, X_train, y_train, cv=3, scoring='accuracy')


    # Calculate metrics
    accuracy = accuracy_score(y_test, y_pred)


    # Store results
    results[name] = {
        'accuracy': accuracy,
        'cv_mean': cv_scores.mean(),
        'cv_std': cv_scores.std(),
        'predictions': y_pred,
        'probabilities': y_pred_proba
    }

    trained_models[name] = classifier

    print(f"  ✅ Accuracy: {accuracy:.4f}")
```

```
    print(f"  📊 CV Score: {cv_scores.mean():.4f} (+/- {cv_scores.std() * 2:.4f})")

print("\n🏆 CLASSIFIER COMPARISON")
print("=" * 50)
comparison_df = pd.DataFrame({
    'Model': list(results.keys()),
    'Test Accuracy': [results[name]['accuracy'] for name in results.keys()],
    'CV Mean': [results[name]['cv_mean'] for name in results.keys()],
    'CV Std': [results[name]['cv_std'] for name in results.keys()]
})

print(comparison_df.round(4))

# Find best model
best_model_name = comparison_df.loc[comparison_df['Test Accuracy'].idxmax(), 'Model']
print(f"\n🥇 Best performing model: {best_model_name}")
```

```
🤖 Training multiple classifiers...

🔄 Training Naive Bayes...
  ✅ Accuracy: 0.9765
  📊 CV Score: 0.9639 (+/- 0.0167)

🔄 Training Logistic Regression...
  ✅ Accuracy: 0.7047
  📊 CV Score: 0.6879 (+/- 0.0698)

🔄 Training SVM...
  ✅ Accuracy: 0.3557
  📊 CV Score: 0.3582 (+/- 0.0363)

🏆 CLASSIFIER COMPARISON
==================================================
                 Model  Test Accuracy  CV Mean  CV Std
0          Naive Bayes         0.9765   0.9639  0.0083
1  Logistic Regression         0.7047   0.6879  0.0349
2                  SVM         0.3557   0.3582  0.0182

🥇 Best performing model: Naive Bayes
```

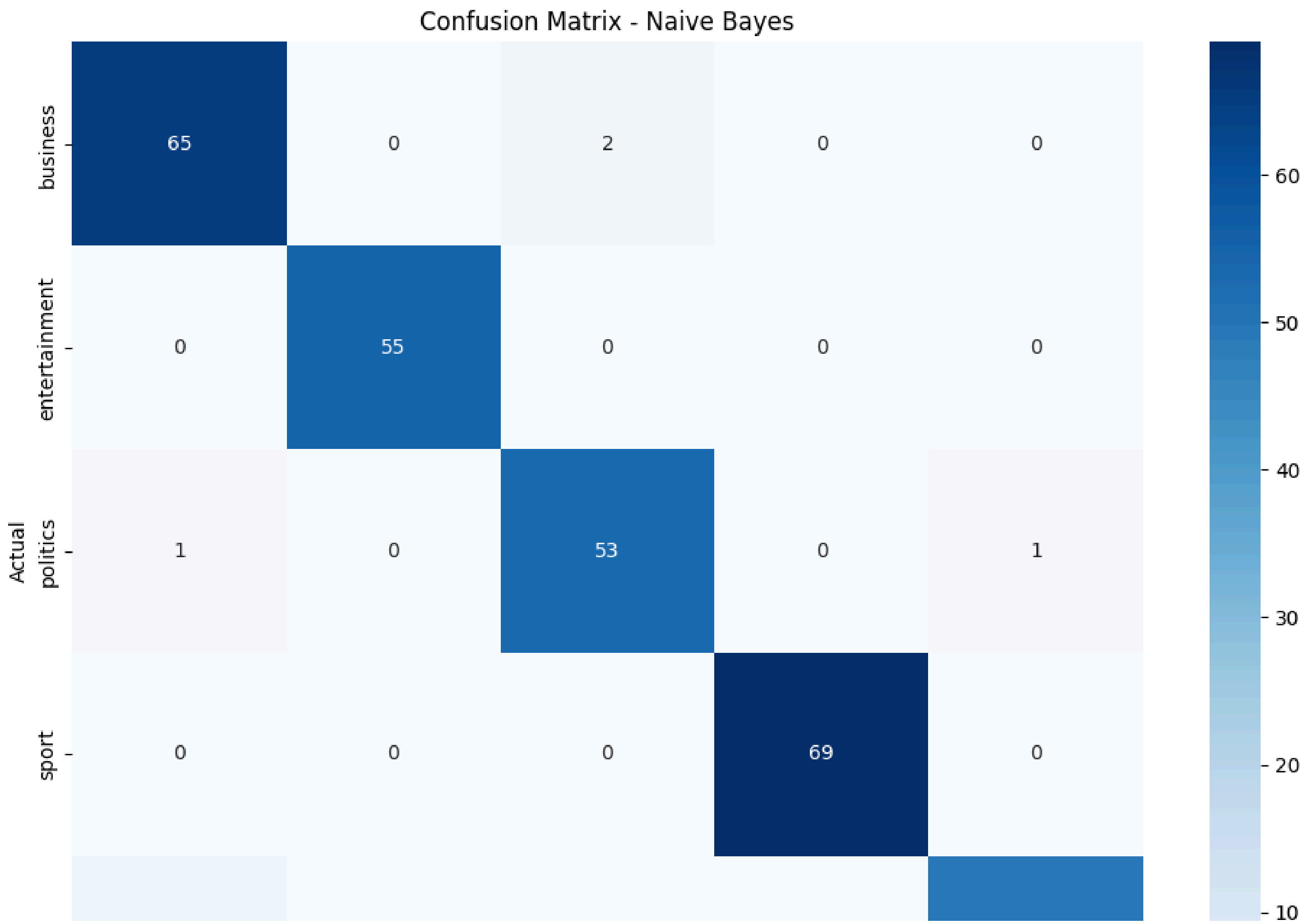
```
# Detailed evaluation of the best model
best_model = trained_models[best_model_name]
best_predictions = results[best_model_name]['predictions']

print(f"📊 DETAILED EVALUATION: {best_model_name}")
print("=" * 60)

# Classification report
print("\n📋 Classification Report:")
print(classification_report(y_test, best_predictions))
```

```
# Confusion matrix
cm = confusion_matrix(y_test, best_predictions)
plt.figure(figsize=(10, 8))
sns.heatmap(cm, annot=True, fmt='d', cmap='Blues',
            xticklabels=np.unique(y), yticklabels=np.unique(y))
plt.title(f'Confusion Matrix - {best_model_name}')
plt.xlabel('Predicted')
plt.ylabel('Actual')
plt.tight_layout()
plt.show()

# Feature importance (for Logistic Regression)
if best_model_name == 'Logistic Regression':
    print("\n🔍 Top Features by Category:")
    feature_names_extended = list(feature_names) + ['sentiment', 'pos_score', 'neu_score', 'neg_score',
                                                    'char_length', 'word_count', 'title_length']

    classes = best_model.classes_
    coefficients = best_model.coef_

    for i, class_name in enumerate(classes):
        top_indices = np.argsort(coefficients[i])[-20:]  # Top 20 features
        print(f"\n📰 {class_name}:")
        for idx in reversed(top_indices):
            if idx < len(feature_names_extended):
                print(f"  {feature_names_extended[idx]}: {coefficients[i][idx]:.4f}")
```

📊 DETAILED EVALUATION: Naive Bayes
==

📋 Classification Report:

	precision	recall	f1-score	support
business	0.94	0.97	0.96	67
entertainment	1.00	1.00	1.00	55
politics	0.96	0.96	0.96	55
sport	1.00	1.00	1.00	69
tech	0.98	0.94	0.96	52
accuracy			0.98	298
macro avg	0.98	0.98	0.98	298
weighted avg	0.98	0.98	0.98	298



🔍 Named Entity Recognition

🎯 Module 8: Extracting Facts from News

Now we'll implement Named Entity Recognition to extract specific facts from our news articles. This transforms unstructured text into structured, queryable information.

NER Applications:

- **Entity Tracking:** Monitor mentions of people, organizations, locations
- **Fact Extraction:** Build knowledge bases from news content
- **Relationship Mapping:** Understand connections between entities
- **Timeline Construction:** Track events and their participants

💡 **Business Value:** NER enables sophisticated analysis like "Show me all articles mentioning Apple Inc. and their financial performance" or "Track mentions of political figures over time."

```
def extract_entities(text):
    """
    Extract named entities using spaCy
    """
    if not text or pd.isna(text):
        return []

    # 🚀 Implement entity extraction
    doc = nlp(str(text))

    entities = []
    for ent in doc.ents:
        entities.append({
            'text': ent.text,
            'label': ent.label_,
            'start': ent.start_char,
            'end': ent.end_char,
            'description': spacy.explain(ent.label_)
        })

    return entities

# Apply NER to all articles
print("🔍 Extracting named entities...")

all_entities = []
```

```python
article_entities = []

for idx, row in df.iterrows():
    entities = extract_entities(row['full_text'])

    # Store entities for this article - Use correct column names
    article_entities.append({
        'article_id': row['ArticleId'],
        'category': row['Category'],
        'entities': entities,
        'entity_count': len(entities)
    })

    # Add to global entity list - Use correct column names
    for entity in entities:
        entity['article_id'] = row['ArticleId']
        entity['category'] = row['Category']
        all_entities.append(entity)

print(f"✅ Entity extraction complete!")
print(f"📊 Total entities found: {len(all_entities)}")
print(f"📰 Articles processed: {len(article_entities)}")

# Convert to DataFrame for analysis
entities_df = pd.DataFrame(all_entities)

if not entities_df.empty:
    print(f"\n🏷️ Entity types found: {entities_df['label'].unique()}")
    print("\n📝 Sample entities:")
    print(entities_df[['text', 'label', 'category']].head(10))
else:
    print("⚠️ No entities found. This might happen with very short sample texts.")
```

```
🔍 Extracting named entities...
✅ Entity extraction complete!
📊 Total entities found: 42031
📰 Articles processed: 1490

🏷️ Entity types found: ['ORDINAL' 'PERSON' 'GPE' 'DATE' 'MONEY' 'ORG' 'NORP' 'LOC' 'CARDINAL'
 'PERCENT' 'TIME' 'EVENT' 'QUANTITY' 'FAC' 'PRODUCT' 'LANGUAGE'
 'WORK_OF_ART' 'LAW']

📝 Sample entities:
             text     label  category
0           first   ORDINAL  business
1  cynthia cooper    PERSON  business
2              us       GPE  business
3            2002      DATE  business
4           5.7bn     MONEY  business
5        new york       GPE  business
```

```
6        wednesday     DATE  business
7  arthur andersen   PERSON  business
8   early 2001 and     DATE  business
9             2002     DATE  business
```

```
# Analyze entity patterns
if not entities_df.empty:
    print("📊 NAMED ENTITY ANALYSIS")
    print("=" * 50)

    # Entity type distribution
    entity_counts = entities_df['label'].value_counts()
    print("\n🏷️ Entity type distribution:")
    print(entity_counts)

    # Entity types by category
    entity_by_category = entities_df.groupby(['category', 'label']).size().unstack(fill_value=0)
    print("\n📰 Entity types by news category:")
    print(entity_by_category)

    # Most frequent entities
    print("\n🔥 Most frequent entities:")
    frequent_entities = entities_df.groupby(['text', 'label']).size().sort_values(ascending=False).head(15)
    for (entity, label), count in frequent_entities.items():
        print(f"  {entity} ({label}): {count} mentions")

    # Visualizations
    fig, axes = plt.subplots(2, 2, figsize=(15, 12))

    # 1. Entity type distribution
    entity_counts.plot(kind='bar', ax=axes[0,0])
    axes[0,0].set_title('Entity Type Distribution')
    axes[0,0].tick_params(axis='x', rotation=45)

    # 2. Entities per category
    entities_per_category = entities_df.groupby('category').size()
    entities_per_category.plot(kind='bar', ax=axes[0,1])
    axes[0,1].set_title('Total Entities per Category')
    axes[0,1].tick_params(axis='x', rotation=45)

    # 3. Entity type heatmap by category
    if entity_by_category.shape[0] > 1 and entity_by_category.shape[1] > 1:
        sns.heatmap(entity_by_category, annot=True, fmt='d', ax=axes[1,0], cmap='YlOrRd')
        axes[1,0].set_title('Entity Types by Category Heatmap')
    else:
        axes[1,0].text(0.5, 0.5, 'Insufficient data\nfor heatmap',
                      ha='center', va='center', transform=axes[1,0].transAxes)
        axes[1,0].set_title('Entity Types by Category')
```

```
    # 4. Top entities
    top_entities = entities_df['text'].value_counts().head(10)
    top_entities.plot(kind='barh', ax=axes[1,1])
    axes[1,1].set_title('Most Mentioned Entities')

    plt.tight_layout()
    plt.show()

    #Entity co-occurence networks
    import spacy
    from collections import defaultdict


    co_occurrence = defaultdict(int)
    # Corrected to use the 'full_text' column from the DataFrame
    for doc_text in df['full_text'].tolist():  # Iterate over text from DataFrame
        # Process each document text with spaCy to get entities
        doc = nlp(doc_text)
        ents = [ent.text for ent in doc.ents]
        for i in range(len(ents)):
            for j in range(i + 1, len(ents)):
                pair = tuple(sorted([ents[i], ents[j]]))
                co_occurrence[pair] += 1


else:
    print("⚠️ Skipping entity analysis due to insufficient data.")
    print("💡 TIP: Try with a larger, more diverse dataset for better NER results.")
```

```
QUANTITY         199
FAC               90
PRODUCT           87
LANGUAGE          61
EVENT             43
LAW               33
WORK_OF_ART        8
Name: count, dtype: int64

📰 Entity types by news category:
label          CARDINAL  DATE  EVENT  FAC   GPE  LANGUAGE  LAW  LOC  MONEY  \
category
business           1036  2413      3   10  1545         1   15  166    906
entertainment      1110  1739     12   15   792         9    4   64    384
politics            823  1359     22   23   944        10    4  120    235
sport              1798  1978      5   40  1505        11    5   33     44
tech               1417  1310      1    2   776        30    5  121    214

label          NORP  ORDINAL   ORG  PERCENT  PERSON  PRODUCT  QUANTITY  TIME  \
category
business        640      178  1394      813     975       22        42    53
entertainment   429      344   645       43    1871        8        20   126
politics        714      217   598      125    1933        3        12    82
sport           640      663   680       18    2518       23        65   241
tech            286      257  1110      277     718       31        60    90

label          WORK_OF_ART
category
business                 1
entertainment            0
politics                 1
sport                    1
tech                     5

🔥 Most frequent entities:
  first (ORDINAL): 767 mentions
  one (CARDINAL): 666 mentions
```

```
two (CARDINAL): 600 mentions
us (GPE): 565 mentions
uk (GPE): 546 mentions
british (NORP): 330 mentions
second (ORDINAL): 325 mentions
three (CARDINAL): 320 mentions
britain (GPE): 285 mentions
london (GPE): 276 mentions
2004 (DATE): 265 mentions
france (GPE): 240 mentions
2005 (DATE): 239 mentions
europe (LOC): 235 mentions
bbc (ORG): 232 mentions
```