```
# Step 1: Import Libraries
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
import re
import string
from sklearn.model_selection import train_test_split, cross_val_score
from sklearn.feature extraction.text import TfidfVectorizer
from sklearn.linear model import LogisticRegression
from sklearn.naive bayes import MultinomialNB
from sklearn.svm import LinearSVC
from sklearn.metrics import classification report, confusion matrix,
accuracy score
import nltk
from nltk.corpus import stopwords
from nltk.stem import WordNetLemmatizer
nltk.download('stopwords')
nltk.download('wordnet')
[nltk data] Downloading package stopwords to /root/nltk data...
[nltk data] Unzipping corpora/stopwords.zip.
[nltk data] Downloading package wordnet to /root/nltk data...
True
# Load dataset
df = pd.read csv('/content/data news.csv')
# Show first few rows
df.head()
{"summary":"{\n \"name\": \"df\",\n \"rows\": 50000,\n \"fields\":
[\n {\n \"column\": \"category\",\n \"properties\": {\n
\"dtype\": \"category\",\n \"num_unique_values\": 10,\n
                        \"BUSINESS\",\n\\"POLITICS\",\n
\"samples\": [\n
\"PARENTING\"\n
]
                     ],\n \"semantic_type\": \"\",\n
                                  },\n {\n \"column\":
\"description\": \"\"\n
                         }\n
\"headline\",\n \"properties\": {\n \"dty
\"string\",\n \"num_unique_values\": 45577,\n
\"samples\": [\n \"These Artists Tried 'Eras
                                          \"dtype\":
                         \"These Artists Tried 'Erasing' Parts Of The
U.S.-Mexico Border Fence\",\n\\"Bugaboo Stroller Recall:
Thousands Of Cameleon3 Strollers Recalled Due To Fall Hazard\",\n
\"Airline Employee's Singing Tribute To Veteran Will Give You
```

```
\"https://www.huffingtonpost.com/entry/tommy-tuberville-dan-patrick-
texas-tech us 5bb6c738e4b097869fd2c796\",\n
\"https://www.huffingtonpost.com/entry/relaxing-in-
texas us 5b9bdd83e4b03a1dcc7ad455\",\n
\"https://www.huffingtonpost.com/entry/the-bachelor-top-hotel-
deals_us_5b9b79cee4b03a1dcc77e70c\"\n
                                              1.\n
\"semantic type\": \"\",\n
                                 \"description\": \"\"\n
                                                                }\
                      \"column\": \"short description\",\n
             {\n
     },\n
\"properties\": {\n
                           \"dtype\": \"string\",\n
\"num_unique_values\": 45743,\n
                                      \"samples\": [\n
\"Check out the two covers below. Do you think the pic was one worth
repeating? IO Donna: Jennifer Lawrence (you might have\",\n
\"Oh you individually wrapped your tacos in twine? They look
delicious!\",\n
                         \"The drama is called \\\"Perfect
Citizen.\\\"\"\n
                        1,\n
                                    \"semantic_type\": \"\",\n
\"description\": \"\"\n
                                                   \"column\":
                             }\n
                                     },\n {\n
\"keywords\",\n \"properties\": {\n
\"string\",\n \"num_unique_values\"
                                                 \"dtvpe\":
                     \"num_unique_values\": 41558,\n
\"samples\": [\n
                          \"typhoon-chan-hom-china\",\n
ryan-gps-guide\",\n
                             \"white-house-takes-big-step-towards-
halting-arctic-drilling\"\n
                                   ],\n
                                               \"semantic type\":
               \"description\": \"\"\n
                                             }\n
                                                    }\n ]\
n}","type":"dataframe","variable name":"df"}
# Combine text fields (headline + short description + keywords)
df['text'] = df['headline'].fillna('') + ' ' +
df['short description'].fillna('') + ' ' + df['keywords'].fillna('')
# Drop unused columns
df = df[['category', 'text']]
# Drop missing or empty values
df.dropna(inplace=True)
df = df[df['text'].str.strip() != '']
# Text Cleaning Function
def clean text(text):
    text = text.lower()
    text = re.sub(r'\[.*?\]', '', text)
    text = re.sub(r'https?://S+|www\.\S+', '', text)
    text = re.sub(r'<.*?>+', '', text)
    text = re.sub(r'[%s]' % re.escape(string.punctuation), '', text)
text = re.sub(r'\n', '', text)
    text = re.sub(r'\w^*\d\w^*', '', text)
    return text
# Apply cleaning
df['clean text'] = df['text'].apply(clean text)
```

```
# Stopwords and Lemmatization
stop = stopwords.words('english')
lemmatizer = WordNetLemmatizer()
def preprocess(text):
    words = text.split()
    words = [lemmatizer.lemmatize(word) for word in words if word not
in stop]
    return ' '.join(words)
df['processed text'] = df['clean text'].apply(preprocess)
# TF-IDF Vectorization
tfidf = TfidfVectorizer(max features=5000)
X = tfidf.fit transform(df['processed text'])
# Target
y = df['category']
# Train-test split
X_train, X_test, y_train, y_test = train_test_split(X, y,
test size=0.2, random state=42)
# Models
models = {
    "Logistic Regression": LogisticRegression(max iter=1000),
    "Naive Bayes": MultinomialNB(),
    "SVM": LinearSVC()
}
# Training and Evaluation
for name, model in models.items():
    print(f"\n{name}")
    model.fit(X_train, y_train)
    preds = model.predict(X test)
    print("Accuracy:", accuracy_score(y_test, preds))
    print("Classification Report:\n", classification report(y test,
preds))
Logistic Regression
Accuracy: 0.7987
Classification Report:
                 precision recall f1-score
                                                  support
      BUSINESS
                     0.73
                               0.78
                                          0.76
                                                     955
 ENTERTAINMENT
                     0.77
                               0.78
                                          0.77
                                                     985
  FOOD & DRINK
                                          0.84
                     0.85
                               0.82
                                                    1021
                               0.76
     PARENTING
                     0.78
                                          0.77
                                                    1030
                     0.79
                               0.74
      POLITICS
                                          0.77
                                                    1034
        SP0RTS
                     0.86
                               0.89
                                          0.88
                                                     995
```

STYLE & BEAUTY					
Maive Bayes	TRAVEL WELLNESS	0.83 0.73	0.80 0.76	0.82 0.74	1008 1009
Accuracy: 0.7831 Classification Report:	macro avg	0.80		0.80	10000
BUSINESS 0.71 0.73 0.72 955 ENTERTAINMENT 0.80 0.74 0.77 985 FOOD & DRINK 0.82 0.85 0.84 1021 PARENTING 0.69 0.74 0.72 1030 POLITICS 0.80 0.73 0.76 1034 SPORTS 0.87 0.86 0.87 995 STYLE & BEAUTY 0.85 0.84 0.85 986 TRAVEL 0.79 0.81 0.80 1008 WELLNESS 0.71 0.72 0.72 1009 WORLD NEWS 0.79 0.81 0.80 977 accuracy 0.78 0.78 0.78 10000 Weighted avg 0.78 0.78 0.78 10000 SVM Accuracy: 0.7914 Classification Report:	Accuracy: 0.783	Report:	recall	fl-score	sunnort
macro avg 0.78 0.78 0.78 10000 SVM Accuracy: 0.7914 Classification Report: precision recall f1-score support BUSINESS 0.74 0.80 0.77 955 ENTERTAINMENT 0.78 0.75 0.77 985 FOOD & DRINK 0.83 0.83 0.83 1021 PARENTING 0.76 0.75 0.76 1030 POLITICS 0.78 0.73 0.75 1034 SPORTS 0.86 0.91 0.89 995 STYLE & BEAUTY 0.84 0.85 0.84 986 TRAVEL 0.81 0.78 0.80 1008 WELLNESS 0.73 0.72 0.72 1009 WORLD NEWS 0.77 0.79 0.78 977 accuracy 0.79 10000	ENTERTAINMENT FOOD & DRINK PARENTING POLITICS SPORTS STYLE & BEAUTY TRAVEL WELLNESS	0.71 0.80 0.82 0.69 0.80 0.87 0.85 0.79	0.73 0.74 0.85 0.74 0.73 0.86 0.84 0.81	0.72 0.77 0.84 0.72 0.76 0.87 0.85 0.80 0.72	955 985 1021 1030 1034 995 986 1008 1009
Accuracy: 0.7914 Classification Report:	macro avg	0.78		0.78	10000
ENTERTAINMENT 0.78 0.75 0.77 985 FOOD & DRINK 0.83 0.83 0.83 1021 PARENTING 0.76 0.75 0.76 1030 POLITICS 0.78 0.73 0.75 1034 SPORTS 0.86 0.91 0.89 995 STYLE & BEAUTY 0.84 0.85 0.84 986 TRAVEL 0.81 0.78 0.80 1008 WELLNESS 0.73 0.72 0.72 1009 WORLD NEWS 0.77 0.79 0.78 977	Accuracy: 0.79	Report:	recall	f1-score	support
·	ENTERTAINMENT FOOD & DRINK PARENTING POLITICS SPORTS STYLE & BEAUTY TRAVEL WELLNESS	0.78 0.83 0.76 0.78 0.86 0.84 0.81 0.73	0.75 0.83 0.75 0.73 0.91 0.85 0.78	0.77 0.83 0.76 0.75 0.89 0.84 0.80 0.72	985 1021 1030 1034 995 986 1008 1009
	_	0.79	0.79		

```
0.79
 weighted avg
                     0.79
                               0.79
                                                   10000
# Save trained models
trained models = {
    "Logistic Regression": models["Logistic Regression"],
    "Naive Bayes": models["Naive Bayes"],
    "SVM": models["SVM"]
}
# Prediction Function
def predict_category(user_input, chosen_model):
    # Clean and preprocess input
    cleaned = clean text(user input)
    processed = preprocess(cleaned)
    # Transform with TF-IDF
    vectorized = tfidf.transform([processed])
    # Predict
    model = trained models.get(chosen model)
    if model:
        prediction = model.predict(vectorized)
        print(f"\nPredicted Category: {prediction[0]}")
    else:
        print("Invalid model choice.")
# Single input from user
print("\nEnter a news article to classify:")
user text = input("Enter text (headline/description/keywords): ")
print("\nChoose a model for prediction:")
print("1. Logistic Regression")
print("2. Naive Bayes")
print("3. SVM")
choice = input("Enter 1, 2, or 3: ")
model map = {
    "\overline{1}": "Logistic Regression",
    "2": "Naive Bayes",
    "3": "SVM"
}
selected model = model map.get(choice)
if selected model:
    predict_category(user_text, selected_model)
    print("Invalid model selection.")
```

Enter a news article to classify:

Enter text (headline/description/keywords): Amazon reports record-breaking quarterly revenue driven by strong e-commerce sales and growth in its cloud computing division, AWS. Analysts project continued expansion as the company invests heavily in logistics and AI infrastructure.

Choose a model for prediction:

- 1. Logistic Regression
- 2. Naive Bayes
- 3. SVM

Enter 1, 2, or 3: 3

Predicted Category: BUSINESS