FINAL PROJECT – GROUP 4

TITLE / CATEGORY:

FAKE NEWS DETECTION (Detect whether a news article is real or fake)

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DATASET SOURCE LINK:

Kaggle Fake News Dataset: https://www.kaggle.com/datasets/algord/fake-news

STEP 1: DATASET SELECTION AND UNDERSTANDING

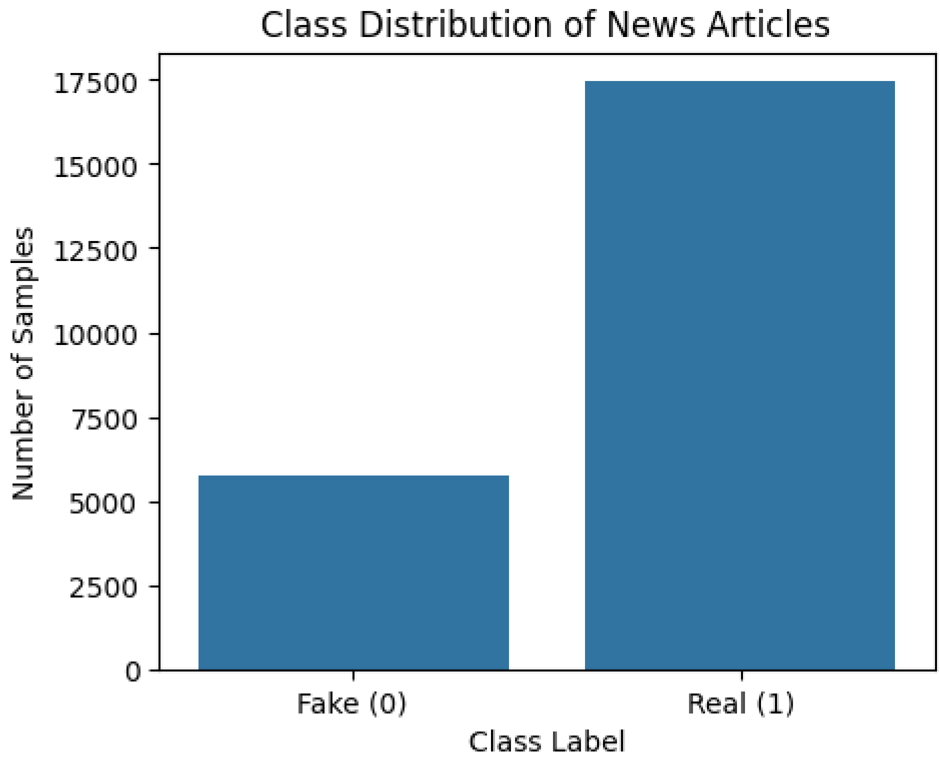
In [1]:
```
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns

# Load Dataset
df = pd.read_csv("/content/FakeNewsNet.csv")

# Dataset Shape
print("DATASET SHAPE:", df.shape)

# Dataset Info
print("\n DATASET STRUCTURE INFORMATION:")
df.info()

# First 5 Rows
print("\n SAMPLE ENTRIES:")
display(df.head())

# Class Distribution
print("\n CLASS DISTRIBUTION:")
print(df['real'].value_counts())
print("\n CLASS DISTRIBUTION PERCENTAGE:")
print(df['real'].value_counts(normalize=True)*100)

# Visualize Class Distribution
plt.figure(figsize=(5,4))
sns.countplot(x='real', data=df)
plt.xticks([0,1], ['Fake (0)', 'Real (1)'])
plt.title("Class Distribution of News Articles")
plt.xlabel("Class Label")
plt.ylabel("Number of Samples")
plt.show()

# Sample Real & Fake Titles
print("\nREAL NEWS TITLE EXAMPLES:")
real_examples = df[df['real'] == 1]['title'].head(10)
```

```python
for i, title in enumerate(real_examples, 1):
    print(f"{i}. {title}")

print("\nFAKE NEWS TITLE EXAMPLES:")
fake_examples = df[df['real'] == 0]['title'].head(10)
for i, title in enumerate(fake_examples, 1):
    print(f"{i}. {title}")

# Title Length Analysis
df['title_length'] = df['title'].astype(str).apply(len)
plt.figure(figsize=(6,4))
sns.histplot(df['title_length'], bins=40, kde=True)
plt.title("Distribution of Title Lengths")
plt.xlabel("Title Length")
plt.ylabel("Frequency")
plt.show()
```

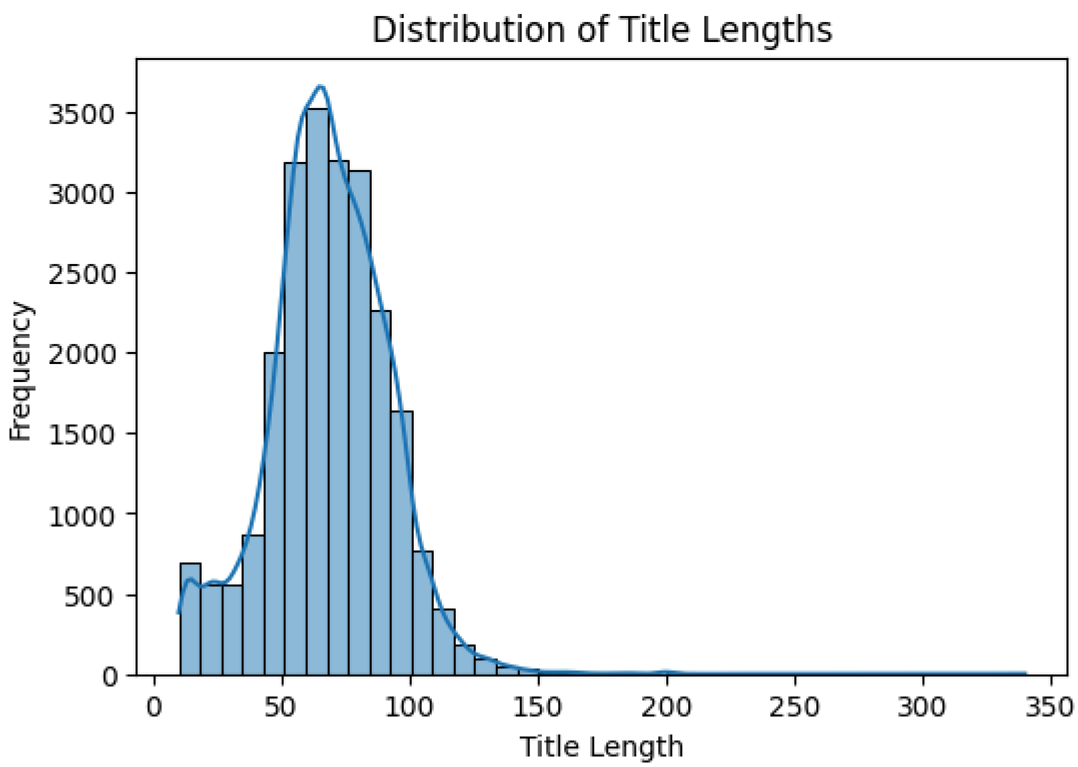
```
DATASET SHAPE: (23196, 5)

 DATASET STRUCTURE INFORMATION:
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 23196 entries, 0 to 23195
Data columns (total 5 columns):
 #   Column         Non-Null Count  Dtype 
---  ------         --------------  ----- 
 0   title          23196 non-null  object
 1   news_url       22866 non-null  object
 2   source_domain  22866 non-null  object
 3   tweet_num      23196 non-null  int64 
 4   real           23196 non-null  int64 
dtypes: int64(2), object(3)
memory usage: 906.2+ KB

 SAMPLE ENTRIES:
```

	title	news_url	source_domain	tweet_r
0	Kandi Burruss Explodes Over Rape Accusation on...	http://toofab.com/2017/05/08/real-housewives-a...	toofab.com	
1	People's Choice Awards 2018: The best red carp...	https://www.today.com/style/see-people-s-choic...	www.today.com	
2	Sophia Bush Sends Sweet Birthday Message to 'O...	https://www.etonline.com/news/220806_sophia_bu...	www.etonline.com	
3	Colombian singer Maluma sparks rumours of inap...	https://www.dailymail.co.uk/news/article-33655...	www.dailymail.co.uk	
4	Gossip Girl 10 Years Later: How Upper East Sid...	https://www.zerchoo.com/entertainment/gossip-g...	www.zerchoo.com	

```
 CLASS DISTRIBUTION:
real
1    17441
0     5755
Name: count, dtype: int64

 CLASS DISTRIBUTION PERCENTAGE:
real
1    75.189688
0    24.810312
Name: proportion, dtype: float64
```




```
REAL NEWS TITLE EXAMPLES:
1. Kandi Burruss Explodes Over Rape Accusation on 'Real Housewives of Atlanta' Re
union (Video)
2. People's Choice Awards 2018: The best red carpet looks
3. Sophia Bush Sends Sweet Birthday Message to 'One Tree Hill' Co-Star Hilarie Bu
rton: 'Breyton 4eva'
4. Colombian singer Maluma sparks rumours of inappropriate relationship with AUNT
5. Gossip Girl 10 Years Later: How Upper East Siders Shocked the World and Change
d Pop Culture Forever
6. Mindy Kaling makes first post-baby appearance at Disneyland with her 'Wrinkle
in Time' co-stars
7. Katharine McPhee Butchers Tony Nominations: “I Have Not Been Drinking”
8. ‘WAGS Miami’ Stars Ashley Nicole Roberts and Philip Wheeler Are Married
9. Medium Tyler Henry Addresses The ‘Chilling’ Messages Kristin Cavallari’s Decea
sed Brother Expressed During Reading
10. DWTS Season 27 Results: Week 5 - Disney Night

FAKE NEWS TITLE EXAMPLES:
1. Gwen Stefani Got Dumped by Blake Shelton Over "Jealousy and Drama" (EXCLUSIVE)
2. Broward County Sheriff Fired For Lying About Parkland
3. Amber Rose Shuts Down French Montana Dating Rumors, Calls Rapper Her 'Bruvaaa'
4. Mel Gibson: Hollywood Pedophiles Have Nowhere Left To Hide
5. 5 Reasons Why Tarek El Moussa Will Overcome His Latest Back Injury
6. The Kardashians donate whopping sum to Las Vegas mass shooting victims
7. Is Brad Pitt Open To Getting Back Together With Angelina After Rumors She’s In
to It?
8. A glimpse at the relationship of Meghan Markle, Kate Middleton, Prince Harry a
nd Prince William before the British royal wedding
9. Are Katie Holmes & Jamie Foxx Expecting A Baby? New Report Claims They Want To
Start A Family
10. Why All Ladies Crush on Angelina Jolie
```



STEP 2: TEXT PREPROCESSING

In [3]:

```
import re
import nltk
import numpy as np
import pandas as pd
from nltk.corpus import stopwords
from nltk.stem import WordNetLemmatizer
from nltk.tokenize import word_tokenize
from sklearn.feature_extraction.text import CountVectorizer, TfidfVectorizer

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

# INITIALIZE STOPWORDS AND LEMMATIZER
stop_words = set(stopwords.words('english'))
lemmatizer = WordNetLemmatizer()

def preprocess_text(text):
    text = str(text).lower()  # Lowercasing
    text = re.sub(r'http\S+|www\S+', '', text)  # Remove URLs
    text = re.sub(r'[^a-z\s]', ' ', text)       # Remove special characters & nu
    tokens = word_tokenize(text)                # Tokenization
    tokens = [word for word in tokens if word not in stop_words]  # Stopword rem
    tokens = [lemmatizer.lemmatize(word) for word in tokens]      # Lemmatizatio
    return " ".join(tokens)

# Display first 5 titles
print("SAMPLE TITLES (FIRST 5 ROWS)")
display(df['title'].head())
print("\n")

# APPLY PREPROCESSING TO TITLES
```

```
df['clean_title'] = df['title'].apply(preprocess_text)

# PRINT FIRST 5 CLEANED TITLES
print("FIRST 5 CLEANED TITLES")
for i, text in enumerate(df['clean_title'].head(), 1):
    print(f"{i}. {text}")

# COUNT VECTORIZER
count_vectorizer = CountVectorizer(ngram_range=(1,2))
count_features = count_vectorizer.fit_transform(df['clean_title'])

print("\n")
print("COUNT VECTORIZER FEATURE MATRIX")
print("Shape:", count_features.shape)
print("Sample Feature Names:", count_vectorizer.get_feature_names_out()[:25])

# TF-IDF VECTORIZER
tfidf_vectorizer = TfidfVectorizer(ngram_range=(1,2))
tfidf_features = tfidf_vectorizer.fit_transform(df['clean_title'])

print("\n")
print("TF-IDF FEATURE MATRIX")
print("Shape:", tfidf_features.shape)
print("Sample TF-IDF Feature Names:", tfidf_vectorizer.get_feature_names_out()[:

print("\n")
print("TF-IDF VECTORS FOR FIRST 5 TITLES IN THE DATASET")

for i, title in enumerate(df['clean_title'].head(), 1):
    vector = tfidf_vectorizer.transform([title]).toarray()[0]
    non_zero_indices = np.where(vector != 0)[0]
    print(f"Title {i}: {df['title'].iloc[i-1]}")
    for idx in non_zero_indices:
        word = tfidf_vectorizer.get_feature_names_out()[idx]
        value = vector[idx]
        print(f"{word:20s} -> {value:.6f}")
    print("-" * 90)
```

```
SAMPLE TITLES (FIRST 5 ROWS)
```

```
[nltk_data] Downloading package punkt to /root/nltk_data...
[nltk_data]   Package punkt is already up-to-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 stopwords to /root/nltk_data...
[nltk_data]   Package stopwords is already up-to-date!
[nltk_data] Downloading package wordnet to /root/nltk_data...
```

	title
0	Kandi Burruss Explodes Over Rape Accusation on...
1	People's Choice Awards 2018: The best red carp...
2	Sophia Bush Sends Sweet Birthday Message to 'O...
3	Colombian singer Maluma sparks rumours of inap...
4	Gossip Girl 10 Years Later: How Upper East Sid...

dtype: object

```
FIRST 5 CLEANED TITLES
1. kandi burruss explodes rape accusation real housewife atlanta reunion video
2. people choice award best red carpet look
3. sophia bush sends sweet birthday message one tree hill co star hilarie burton
breyton eva
4. colombian singer maluma spark rumour inappropriate relationship aunt
5. gossip girl year later upper east siders shocked world changed pop culture for
ever


COUNT VECTORIZER FEATURE MATRIX
Shape: (23196, 115708)
Sample Feature Names: ['aaliyah' 'aaliyah alleged' 'aaliyah fashion' 'aaliyah hal
loween'
 'aaliyah mac' 'aaron' 'aaron armstrong' 'aaron bass' 'aaron carter'
 'aaron hernandez' 'aaron lohr' 'aaron paul' 'aaron rodgers'
 'aaron sorkin' 'ab' 'ab add' 'ab beard' 'ab belly' 'ab british'
 'ab cleavage' 'ab fixed' 'ab michelob' 'ab photo' 'ab seven' 'ab simple']


TF-IDF FEATURE MATRIX
Shape: (23196, 115708)
Sample TF-IDF Feature Names: ['aaliyah' 'aaliyah alleged' 'aaliyah fashion' 'aali
yah halloween'
 'aaliyah mac' 'aaron' 'aaron armstrong' 'aaron bass' 'aaron carter'
 'aaron hernandez' 'aaron lohr' 'aaron paul' 'aaron rodgers'
 'aaron sorkin' 'ab' 'ab add' 'ab beard' 'ab belly' 'ab british'
 'ab cleavage' 'ab fixed' 'ab michelob' 'ab photo' 'ab seven' 'ab simple']


TF-IDF VECTORS FOR FIRST 5 TITLES IN THE DATASET
Title 1: Kandi Burruss Explodes Over Rape Accusation on 'Real Housewives of Atlan
ta' Reunion (Video)
accusation          -> 0.213215
accusation real     -> 0.281966
atlanta             -> 0.196617
atlanta reunion     -> 0.263098
burruss             -> 0.247865
burruss explodes    -> 0.281966
explodes            -> 0.241024
explodes rape       -> 0.281966
housewife           -> 0.165934
housewife atlanta   -> 0.225363
kandi               -> 0.247865
kandi burruss       -> 0.247865
rape                -> 0.199093
rape accusation     -> 0.281966
real                -> 0.148142
real housewife      -> 0.167717
reunion             -> 0.162686
reunion video       -> 0.270929
video               -> 0.135398
--------------------------------------------------------------------------------
---------
Title 2: People's Choice Awards 2018: The best red carpet looks
award               -> 0.191852
award best          -> 0.363316
best                -> 0.210179
best red            -> 0.386174
```

```
carpet               -> 0.240541
carpet look          -> 0.359921
choice               -> 0.262270
choice award         -> 0.272975
look                 -> 0.212536
people               -> 0.245953
people choice        -> 0.297986
red                  -> 0.234031
red carpet           -> 0.240737
--------------------------------------------------------------------------------------
---------
Title 3: Sophia Bush Sends Sweet Birthday Message to 'One Tree Hill' Co-Star Hila
rie Burton: 'Breyton 4eva'
birthday             -> 0.116584
birthday message     -> 0.179385
breyton              -> 0.226095
breyton eva          -> 0.226095
burton               -> 0.198751
burton breyton       -> 0.226095
bush                 -> 0.160708
bush sends           -> 0.226095
co                   -> 0.136548
co star              -> 0.147578
eva                  -> 0.150793
hilarie              -> 0.198751
hilarie burton       -> 0.198751
hill                 -> 0.145040
hill co              -> 0.217245
message              -> 0.140063
message one          -> 0.226095
one                  -> 0.121239
one tree             -> 0.210966
sends                -> 0.172787
sends sweet          -> 0.226095
sophia               -> 0.170111
sophia bush          -> 0.195837
star                 -> 0.089573
star hilarie         -> 0.226095
sweet                -> 0.139644
sweet birthday       -> 0.198751
tree                 -> 0.182116
tree hill            -> 0.210966
--------------------------------------------------------------------------------------
---------
Title 4: Colombian singer Maluma sparks rumours of inappropriate relationship wit
h AUNT
aunt                 -> 0.246052
colombian            -> 0.274814
colombian singer     -> 0.294522
inappropriate        -> 0.241302
inappropriate relationship -> 0.294522
maluma               -> 0.246052
maluma spark         -> 0.294522
relationship         -> 0.151401
relationship aunt    -> 0.294522
rumour               -> 0.216593
rumour inappropriate -> 0.294522
singer               -> 0.183868
singer maluma        -> 0.294522
spark                -> 0.202438
```

```
spark rumour          -> 0.282994
------------------------------------------------------------------------------------------
Title 5: Gossip Girl 10 Years Later: How Upper East Siders Shocked the World and Changed Pop Culture Forever
changed               -> 0.163653
changed pop           -> 0.236084
culture               -> 0.193424
culture forever       -> 0.236084
east                  -> 0.183606
east siders           -> 0.236084
forever               -> 0.177626
girl                  -> 0.125501
girl year             -> 0.226843
gossip                -> 0.162722
gossip girl           -> 0.193424
later                 -> 0.180420
later upper           -> 0.236084
pop                   -> 0.167808
pop culture           -> 0.211045
shocked               -> 0.183606
shocked world         -> 0.236084
siders                -> 0.236084
siders shocked        -> 0.236084
upper                 -> 0.182494
upper east            -> 0.236084
world                 -> 0.138300
world changed         -> 0.236084
year                  -> 0.106511
year later            -> 0.187310
------------------------------------------------------------------------------------------
```

STEP 3: MODEL BUILDING

In [4]:

```
import pandas as pd
from sklearn.model_selection import train_test_split
from sklearn.feature_extraction.text import TfidfVectorizer
from sklearn.naive_bayes import MultinomialNB
from sklearn.linear_model import LogisticRegression
from sklearn.svm import LinearSVC

df['clean_title'] = df['title'].apply(preprocess_text)
print("All titles cleaned and saved to 'clean_title' column.")
print(df[['title', 'clean_title']].head(5))

# Use preprocessed titles
X = df['clean_title']
y = df['real']

# TRAIN-TEST SPLIT (80/20)
X_train, X_test, y_train, y_test = train_test_split(
    X, y, test_size=0.20, random_state=42, stratify=y
)

print("\n")
print("Training samples:", X_train.shape[0])
print("Testing samples :", X_test.shape[0])

# TF-IDF FEATURE EXTRACTION
```

```
tfidf_vectorizer = TfidfVectorizer(ngram_range=(1,2))
X_train_tfidf = tfidf_vectorizer.fit_transform(X_train)
X_test_tfidf  = tfidf_vectorizer.transform(X_test)

print("TF-IDF Train Shape:", X_train_tfidf.shape)
print("TF-IDF Test Shape :", X_test_tfidf.shape)

# TRAIN MODELS USING ML ALGORITHMS

# 1. Multinomial Naive Bayes
nb_model = MultinomialNB()
nb_model.fit(X_train_tfidf, y_train)
nb_pred = nb_model.predict(X_test_tfidf)
print("\nMultinomial Naive Bayes model trained successfully!")

# 2. Logistic Regression
lr_model = LogisticRegression(max_iter=1000)
lr_model.fit(X_train_tfidf, y_train)
lr_pred = lr_model.predict(X_test_tfidf)
print("Logistic Regression model trained successfully!")

# 3. Support Vector Machine (Linear SVC)
svm_model = LinearSVC()
svm_model.fit(X_train_tfidf, y_train)
svm_pred = svm_model.predict(X_test_tfidf)
print("Support Vector Machine (SVM) model trained successfully!")

print("\nAll models have been trained and predictions are ready.")
```

```
All titles cleaned and saved to 'clean_title' column.
                                               title  \
0  Kandi Burruss Explodes Over Rape Accusation on...
1  People's Choice Awards 2018: The best red carp...
2  Sophia Bush Sends Sweet Birthday Message to 'O...
3  Colombian singer Maluma sparks rumours of inap...
4  Gossip Girl 10 Years Later: How Upper East Sid...

                                         clean_title
0  kandi burruss explodes rape accusation real ho...
1           people choice award best red carpet look
2  sophia bush sends sweet birthday message one t...
3  colombian singer maluma spark rumour inappropr...
4  gossip girl year later upper east siders shock...


Training samples: 18556
Testing samples : 4640
TF-IDF Train Shape: (18556, 96935)
TF-IDF Test Shape : (4640, 96935)

Multinomial Naive Bayes model trained successfully!
Logistic Regression model trained successfully!
Support Vector Machine (SVM) model trained successfully!

All models have been trained and predictions are ready.
```

STEP 4: EVALUATION

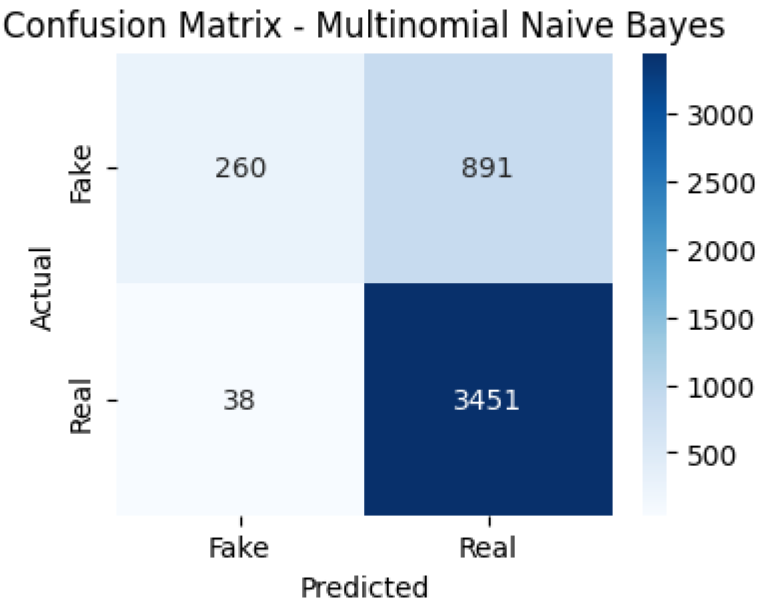
In [5]:
```
import matplotlib.pyplot as plt
import seaborn as sns
```

```python
from sklearn.metrics import accuracy_score, precision_score, recall_score, f1_sc
from sklearn.metrics.pairwise import cosine_similarity
from sklearn.decomposition import PCA
import numpy as np

# EVALUATION FUNCTION
def evaluate_model(y_true, y_pred, model_name):
    acc = accuracy_score(y_true, y_pred)
    prec = precision_score(y_true, y_pred)
    rec = recall_score(y_true, y_pred)
    f1 = f1_score(y_true, y_pred)

    print(f"\n========== Evaluation Metrics for {model_name} ==========")
    print(f"Accuracy : {acc:.6f}")
    print(f"Precision: {prec:.6f}")
    print(f"Recall   : {rec:.6f}")
    print(f"F1-Score : {f1:.6f}")

    # Confusion Matrix
    cm = confusion_matrix(y_true, y_pred)
    plt.figure(figsize=(4,3))
    sns.heatmap(cm, annot=True, fmt='d', cmap='Blues',
                xticklabels=['Fake', 'Real'],
                yticklabels=['Fake', 'Real'])
    plt.title(f"Confusion Matrix - {model_name}")
    plt.xlabel("Predicted")
    plt.ylabel("Actual")
    plt.show()

    return acc, prec, rec, f1

# EVALUATE ALL MODELS
evaluate_model(y_test, nb_pred, "Multinomial Naive Bayes")
evaluate_model(y_test, lr_pred, "Logistic Regression")
evaluate_model(y_test, svm_pred, "Support Vector Machine (SVM)")

# ACCURACY COMPARISON
accuracy_values = [
    accuracy_score(y_test, nb_pred),
    accuracy_score(y_test, lr_pred),
    accuracy_score(y_test, svm_pred)
]
model_names = ["Naive Bayes", "Logistic Regression", "SVM"]

plt.figure(figsize=(7,4))
sns.barplot(x=model_names, y=accuracy_values)
plt.ylim(0,1)
plt.title("Accuracy Comparison of Models")
plt.ylabel("Accuracy")
plt.show()

# SEMANTIC SIMILARITY (COSINE SIMILARITY)
sample_titles = df['clean_title'].iloc[:10]
sample_vectors = tfidf_vectorizer.transform(sample_titles)
cos_sim_matrix = cosine_similarity(sample_vectors)

print("\nSample Titles:\n")
for i, title in enumerate(sample_titles):
    print(f"{i+1}. {title}")
```

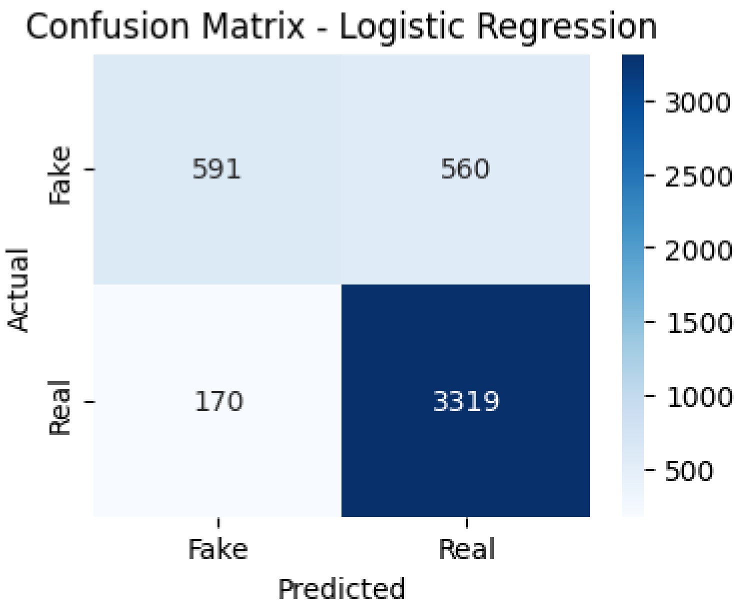
```
print("\nCosine Similarity Matrix:\n")
print(np.round(cos_sim_matrix, 2))

# PCA (Principal Component Analysis) EMBEDDING VISUALIZATION
sample_idx = np.random.choice(X_test_tfidf.shape[0], min(400, X_test_tfidf.shape
X_sample = X_test_tfidf[sample_idx].toarray()
y_sample = y_test.iloc[sample_idx]

pca = PCA(n_components=2, random_state=42)
X_2d = pca.fit_transform(X_sample)

plt.figure(figsize=(7,6))
scatter = plt.scatter(X_2d[:,0], X_2d[:,1], c=y_sample, cmap='coolwarm', alpha=0
plt.title("PCA Projection of TF-IDF Embeddings")
plt.xlabel("Principal Component 1")
plt.ylabel("Principal Component 2")
plt.colorbar(scatter, label="Class (0 = Fake, 1 = Real)")
plt.show()

# Plot Embedding using t-SNE
from sklearn.manifold import TSNE

# Subset Sample
sample_idx = np.random.choice(X_test_tfidf.shape[0], min(500, X_test_tfidf.shape
X_sample_tsne = X_test_tfidf[sample_idx].toarray()
y_sample_tsne = y_test.iloc[sample_idx]

# t-SNE projection
tsne = TSNE(n_components=2, random_state=42, perplexity=40, max_iter=1000)
X_tsne = tsne.fit_transform(X_sample_tsne)

plt.figure(figsize=(8,6))
scatter = plt.scatter(X_tsne[:,0], X_tsne[:,1], c=y_sample_tsne, cmap='coolwarm'
plt.title("t-SNE Projection of TF-IDF Embeddings")
plt.xlabel("t-SNE Component 1")
plt.ylabel("t-SNE Component 2")
plt.colorbar(scatter, label="Class (0 = Fake, 1 = Real)")
plt.show()

# SEMANTIC CLOSENESS OF RELATED WORDS
print("\nSemantic Closeness of Related Words")

related_words = ["government", "policy", "election"]

feature_names = tfidf_vectorizer.get_feature_names_out()

existing_words = [w for w in related_words if w in feature_names]

# If some of the selected words are not present in the TF-IDF vocabulary, automa
if len(existing_words) < len(related_words):
    print("Some words are missing from the vocabulary. Selecting top TF-IDF word

    # Top 50 vocabulary words
    important_words = list(feature_names[:50])
    existing_words = important_words[:5]   # pick top 5 for similarity analysis
    print("Using these dynamic words:", existing_words)

# Computing similarity for the selected words
word_vectors = tfidf_vectorizer.transform(existing_words).toarray()
word_similarity = cosine_similarity(word_vectors)
```

```
print("\nCosine Similarity Between Words:")
print(np.round(word_similarity, 2))

# Heatmap
plt.figure(figsize=(5, 4))
sns.heatmap(word_similarity, annot=True, xticklabels=existing_words,
            yticklabels=existing_words, cmap='coolwarm')
plt.title("Semantic Closeness of Related Words")
plt.show()
```

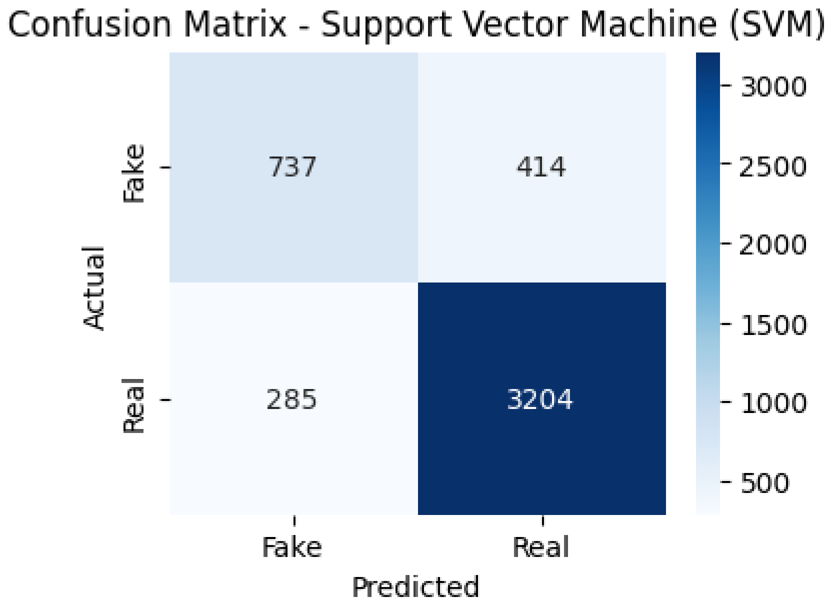
```
========== Evaluation Metrics for Multinomial Naive Bayes ==========
Accuracy : 0.799784
Precision: 0.794795
Recall   : 0.989109
F1-Score : 0.881369
```

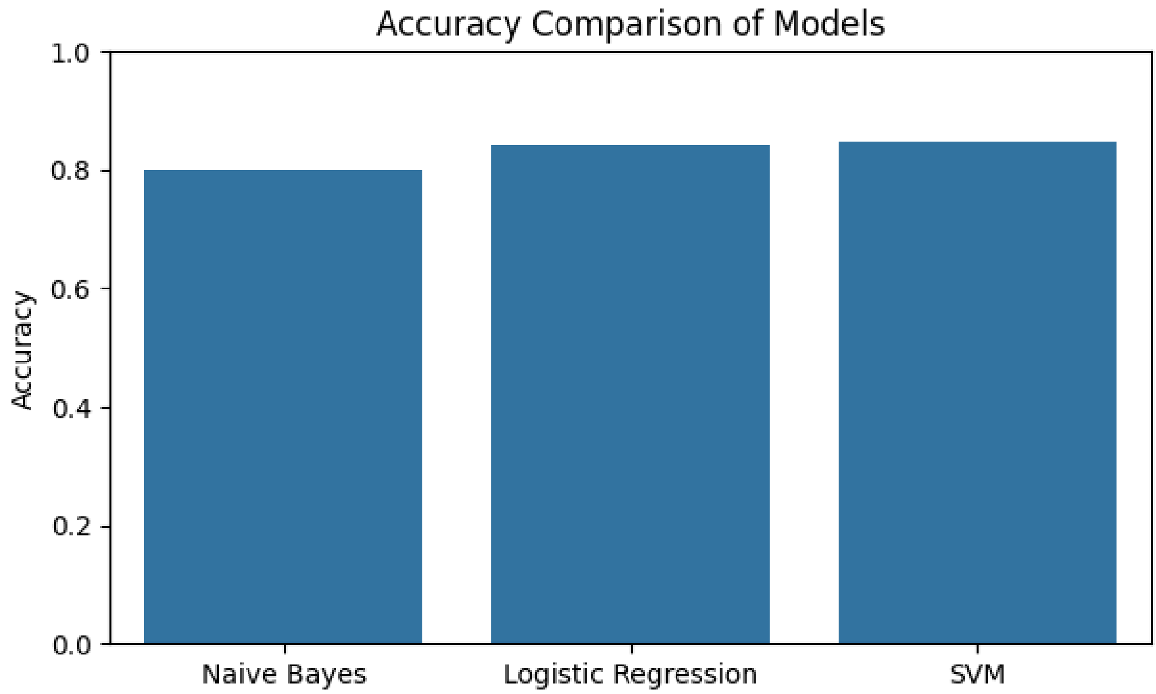



```
========== Evaluation Metrics for Logistic Regression ==========
Accuracy : 0.842672
Precision: 0.855633
Recall   : 0.951275
F1-Score : 0.900923
```

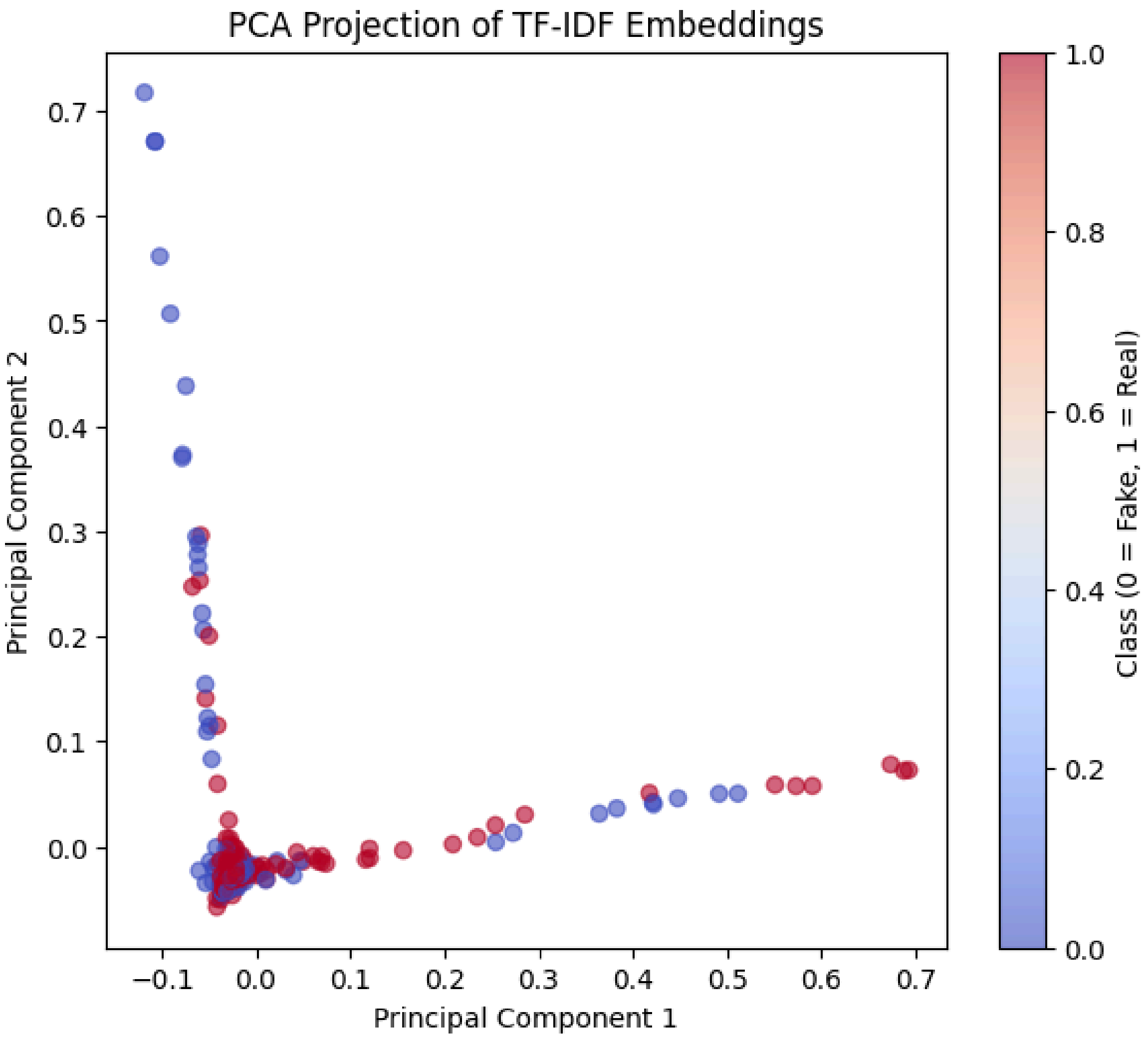


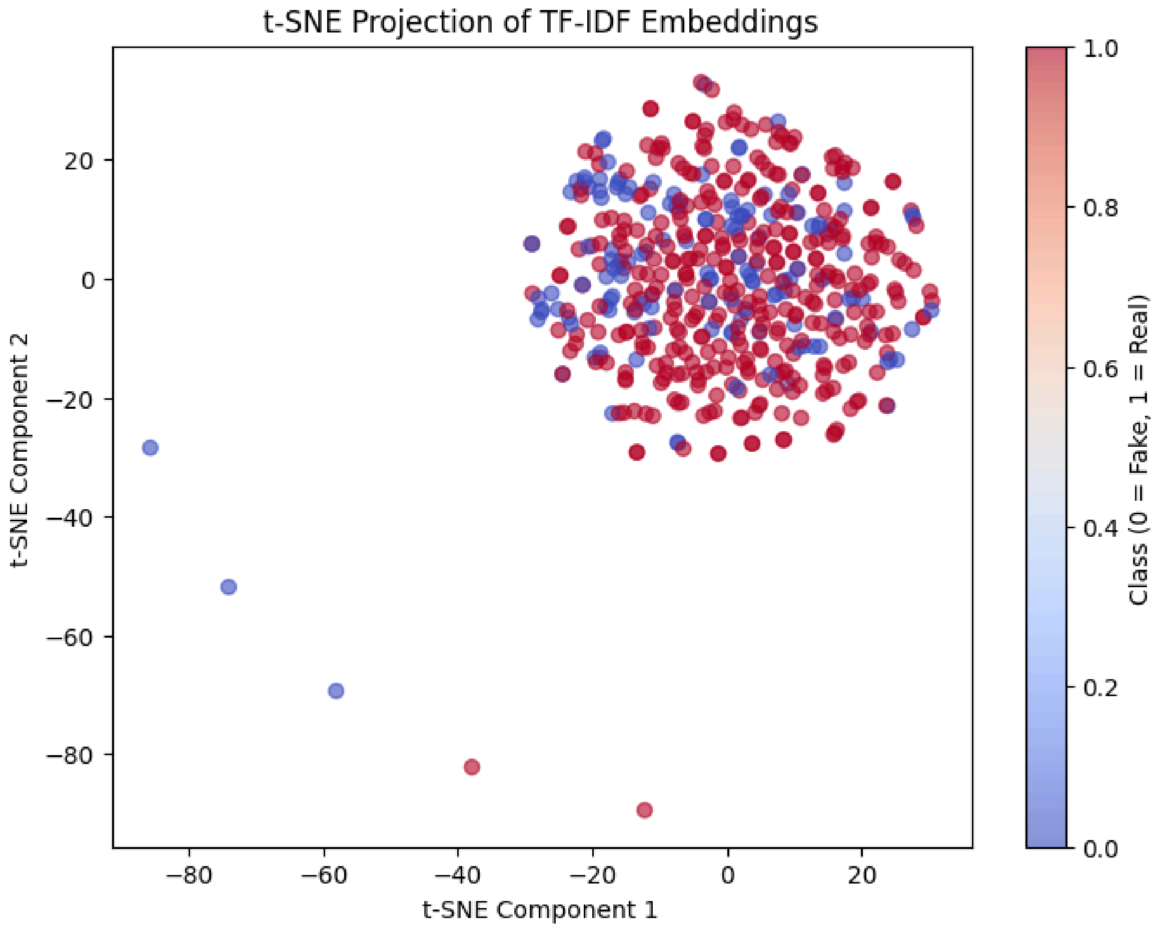
```
========== Evaluation Metrics for Support Vector Machine (SVM) ==========
Accuracy : 0.849353
Precision: 0.885572
Recall   : 0.918315
F1-Score : 0.901646
```



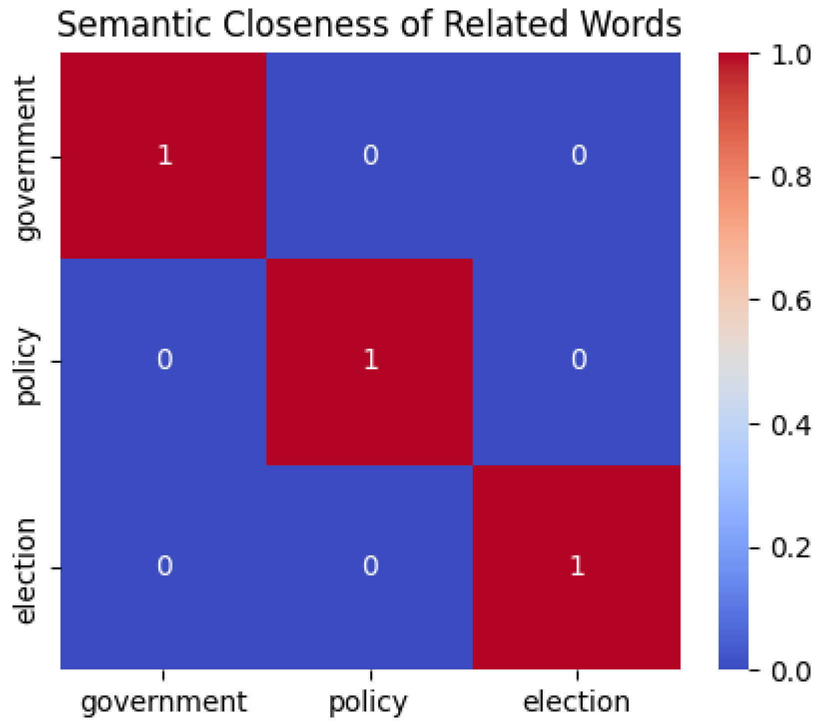


```
Sample Titles:

1. kandi burruss explodes rape accusation real housewife atlanta reunion video
2. people choice award best red carpet look
3. sophia bush sends sweet birthday message one tree hill co star hilarie burton breyton eva
4. colombian singer maluma spark rumour inappropriate relationship aunt
5. gossip girl year later upper east siders shocked world changed pop culture for ever
6. gwen stefani got dumped blake shelton jealousy drama exclusive
7. broward county sheriff fired lying parkland
8. amber rose shuts french montana dating rumor call rapper bruvaaa
9. mindy kaling make first post baby appearance disneyland wrinkle time co star
10. katharine mcphee butcher tony nomination drinking

Cosine Similarity Matrix:

[[1.   0.   0.   0.   0.   0.   0.   0.   0.   0.  ]
 [0.   1.   0.   0.   0.   0.   0.   0.   0.   0.  ]
 [0.   0.   1.   0.   0.   0.   0.   0.   0.06 0.  ]
 [0.   0.   0.   1.   0.   0.   0.   0.   0.   0.  ]
 [0.   0.   0.   0.   1.   0.   0.   0.   0.   0.  ]
 [0.   0.   0.   0.   0.   1.   0.   0.   0.   0.  ]
 [0.   0.   0.   0.   0.   0.   1.   0.   0.   0.  ]
 [0.   0.   0.   0.   0.   0.   0.   1.   0.   0.  ]
 [0.   0.   0.06 0.   0.   0.   0.   0.   1.   0.  ]
 [0.   0.   0.   0.   0.   0.   0.   0.   0.   1.  ]]
```






```
Semantic Closeness of Related Words

Cosine Similarity Between Words:
[[1. 0. 0.]
 [0. 1. 0.]
 [0. 0. 1.]]
```



STEP 5: FINAL RESULT

In [6]:
```
import pandas as pd
import numpy as np
import re
import matplotlib.pyplot as plt
import seaborn as sns
from nltk.corpus import stopwords
from nltk.stem import WordNetLemmatizer
from nltk.tokenize import word_tokenize
from sklearn.feature_extraction.text import TfidfVectorizer
from sklearn.model_selection import train_test_split
from sklearn.naive_bayes import MultinomialNB
from sklearn.linear_model import LogisticRegression
from sklearn.svm import LinearSVC
from sklearn.metrics import accuracy_score, precision_score, recall_score, f1_sc

import nltk
nltk.download('punkt')
nltk.download('punkt_tab')
nltk.download('stopwords')
nltk.download('wordnet')

# df = pd.read_csv("/content/FakeNewsNet.csv")

stop_words = set(stopwords.words('english'))
lemmatizer = WordNetLemmatizer()

# Strategy 1: Basic Preprocessing
def preprocess_strategy1(text):
    text = str(text).lower() # Lowercasing
    text = re.sub(r'http\S+|www\S+', '', text) # Remove URLs
    text = re.sub(r'[^a-z\s]', ' ', text) # Remove special characters & numbers
    tokens = word_tokenize(text) # Tokenization
    tokens = [w for w in tokens if w not in stop_words] # Stopword removal
    return " ".join(tokens)

# Strategy 2: Preprocessing + Lemmatization or Stemming
def preprocess_strategy2(text):
    text = str(text).lower() # Lowercasing
    text = re.sub(r'http\S+|www\S+', '', text) # Remove URLs
    text = re.sub(r'[^a-z\s]', ' ', text) # Remove special characters & numbers
    tokens = word_tokenize(text) # Tokenization
    tokens = [w for w in tokens if w not in stop_words] # Stopword removal
    tokens = [lemmatizer.lemmatize(w) for w in tokens] # Lemmatization or Stemmi
    return " ".join(tokens)

# Apply preprocessing
df['clean_title_s1'] = df['title'].apply(preprocess_strategy1)
df['clean_title_s2'] = df['title'].apply(preprocess_strategy2)

# TRAIN-TEST SPLIT
y = df['real']

X_s1_train, X_s1_test, y_train, y_test = train_test_split(
    df['clean_title_s1'], y, test_size=0.2, random_state=42, stratify=y
)

X_s2_train, X_s2_test, _, _ = train_test_split(
    df['clean_title_s2'], y, test_size=0.2, random_state=42, stratify=y
)
```

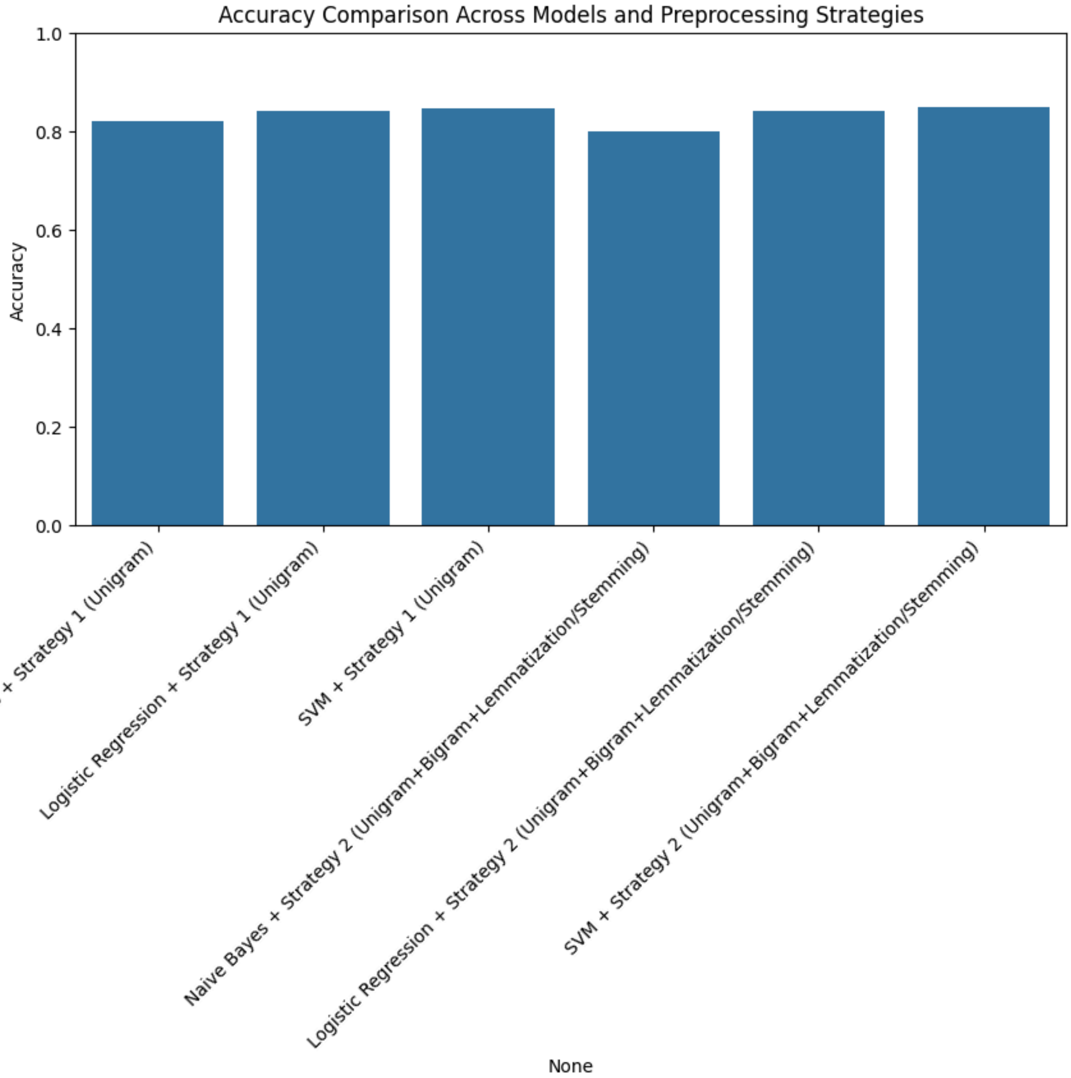
```
# TF-IDF VECTORIZE BOTH STRATEGIES
tfidf_s1 = TfidfVectorizer(ngram_range=(1,1))  # Unigrams
X_s1_train_tfidf = tfidf_s1.fit_transform(X_s1_train)
X_s1_test_tfidf = tfidf_s1.transform(X_s1_test)

tfidf_s2 = TfidfVectorizer(ngram_range=(1,2))  # Unigrams + Bigrams
X_s2_train_tfidf = tfidf_s2.fit_transform(X_s2_train)
X_s2_test_tfidf = tfidf_s2.transform(X_s2_test)

# TRAIN AND EVALUATE MODELS
models = {
    "Naive Bayes": MultinomialNB(),
    "Logistic Regression": LogisticRegression(max_iter=1000),
    "SVM": LinearSVC()
}

results = {}

for strategy_name, X_train_vec, X_test_vec in [
    ("Strategy 1 (Unigram)", X_s1_train_tfidf, X_s1_test_tfidf),
    ("Strategy 2 (Unigram+Bigram+Lemmatization/Stemming)", X_s2_train_tfidf, X_s
]:
    for model_name, model in models.items():
        model.fit(X_train_vec, y_train)
        y_pred = model.predict(X_test_vec)

        acc = accuracy_score(y_test, y_pred)
        prec = precision_score(y_test, y_pred)
        rec = recall_score(y_test, y_pred)
        f1 = f1_score(y_test, y_pred)

        results[f"{model_name} + {strategy_name}"] = {
            "Accuracy": round(acc, 4),
            "Precision": round(prec, 4),
            "Recall": round(rec, 4),
            "F1-Score": round(f1, 4)
        }

# RESULTS TABLE
results_df = pd.DataFrame(results).T
print("COMPARISON OF ML MODELS AND PREPROCESSING STRATEGIES")
display(results_df)

# VISUALIZE RESULTS
# Plot Accuracy, Precision, Recall, F1-Score for all model-strategy combinations
metrics = ['Accuracy', 'Precision', 'Recall', 'F1-Score']
for metric in metrics:
    plt.figure(figsize=(10,5))
    sns.barplot(x=results_df.index, y=results_df[metric])
    plt.xticks(rotation=45, ha='right')
    plt.ylim(0,1)
    plt.title(f"{metric} Comparison Across Models and Preprocessing Strategies")
    plt.ylabel(metric)
    plt.show()

print("\nComparison of Results\n")
print("1. Comparison between Two Preprocessing Strategies:")
print("- Strategy 1 Basic preprocessing: {(Lowercasing, Handling special charact
```

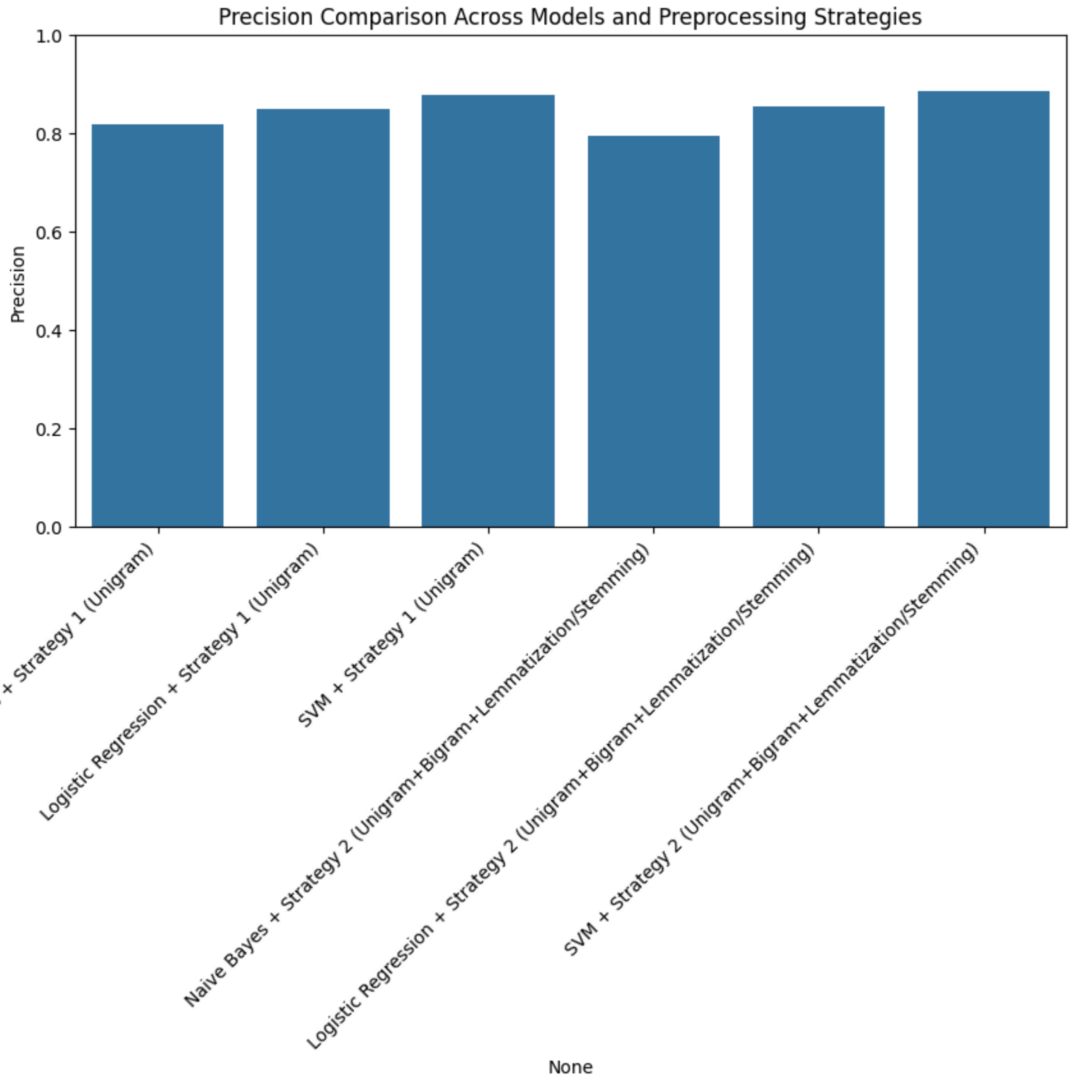
```
print("\n2. Comparison between Different Machine Learning Models:")
print("- Logistic Regression and SVM generally achieve higher accuracy and F1-sc
print("- Naive Bayes is still competitive and faster, but slightly less accurate
print("\n")

# CONFUSION MATRIX (Example: Logistic Regression + Strategy 2)
model = LogisticRegression(max_iter=1000)
model.fit(X_s2_train_tfidf, y_train)
y_pred = model.predict(X_s2_test_tfidf)

cm = confusion_matrix(y_test, y_pred)
plt.figure(figsize=(4,3))
sns.heatmap(cm, annot=True, fmt='d', cmap='Blues',
            xticklabels=['Fake', 'Real'], yticklabels=['Fake', 'Real'])
plt.title("Confusion Matrix - Logistic Regression (Strategy 2)")
plt.xlabel("Predicted")
plt.ylabel("Actual")
plt.show()

# SEMANTIC SIMILARITY
sample_titles = df['clean_title_s2'].head(5)
sample_vectors = tfidf_s2.transform(sample_titles)
cos_sim_matrix = cosine_similarity(sample_vectors)
print("Cosine Similarity Matrix:\n", np.round(cos_sim_matrix,2))

# PCA VISUALIZATION
sample_idx = np.random.choice(X_s2_test_tfidf.shape[0], min(300, X_s2_test_tfidf
X_sample = X_s2_test_tfidf[sample_idx].toarray()
y_sample = y_test.iloc[sample_idx]

pca = PCA(n_components=2, random_state=42)
X_2d = pca.fit_transform(X_sample)

plt.figure(figsize=(7,6))
plt.scatter(X_2d[:,0], X_2d[:,1], c=y_sample, cmap='coolwarm', alpha=0.6)
plt.title("PCA Projection of TF-IDF Embeddings")
plt.xlabel("Principal Component 1")
plt.ylabel("Principal Component 2")
plt.colorbar(label="Class (0=Fake, 1=Real)")
plt.show()

# t-SNE VISUALIZATION
tsne = TSNE(n_components=2, random_state=42, perplexity=40, max_iter=1000)
X_tsne = tsne.fit_transform(X_sample)
plt.figure(figsize=(8,6))
plt.scatter(X_tsne[:,0], X_tsne[:,1], c=y_sample, cmap='coolwarm', alpha=0.6)
plt.title("t-SNE Projection of TF-IDF Embeddings")
plt.xlabel("t-SNE Component 1")
plt.ylabel("t-SNE Component 2")
plt.colorbar(label="Class (0=Fake, 1=Real)")
plt.show()
```

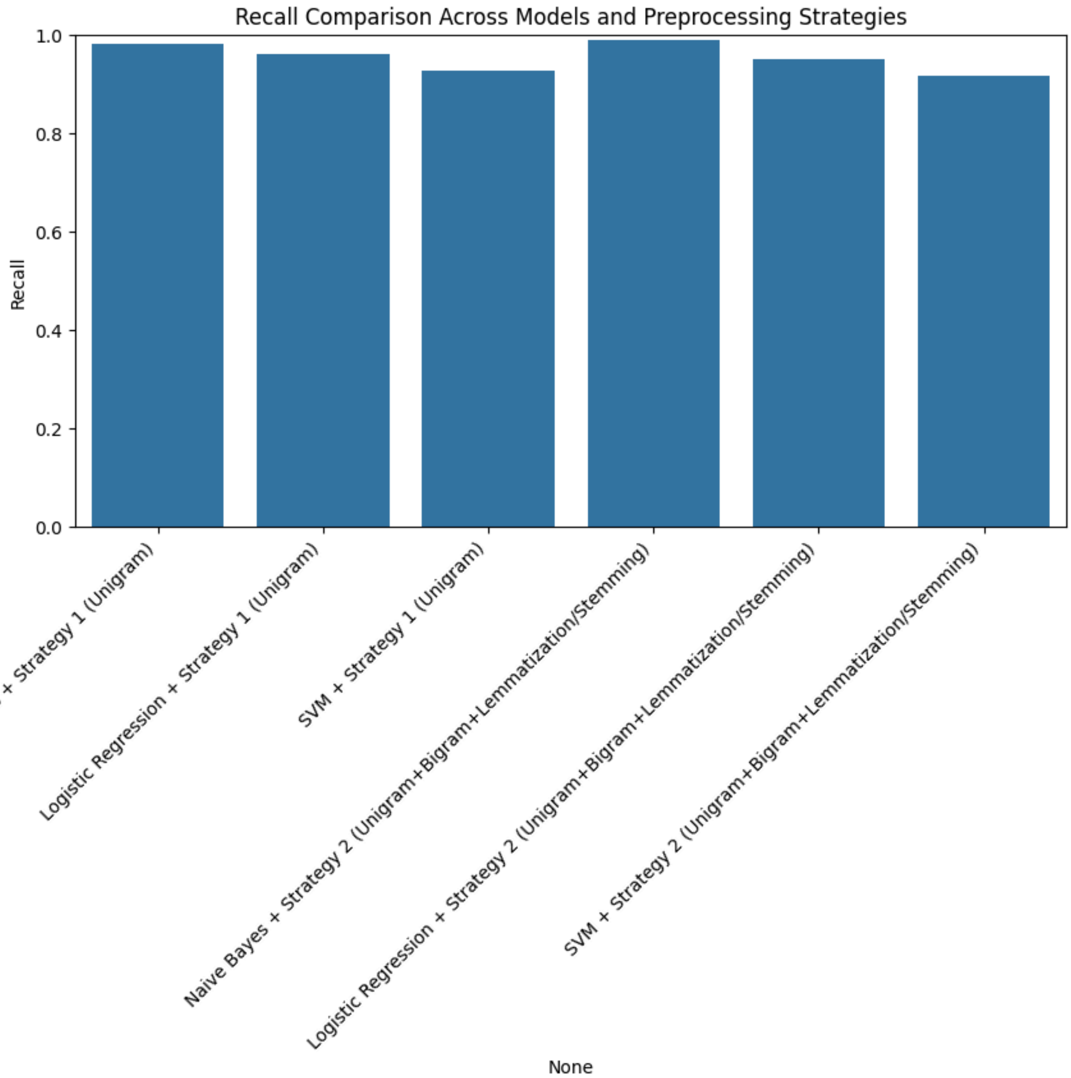
```
[nltk_data] Downloading package punkt to /root/nltk_data...
[nltk_data]   Package punkt is already up-to-date!
[nltk_data] Downloading package punkt_tab to /root/nltk_data...
[nltk_data]   Package punkt_tab is already up-to-date!
[nltk_data] Downloading package stopwords to /root/nltk_data...
[nltk_data]   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!
```

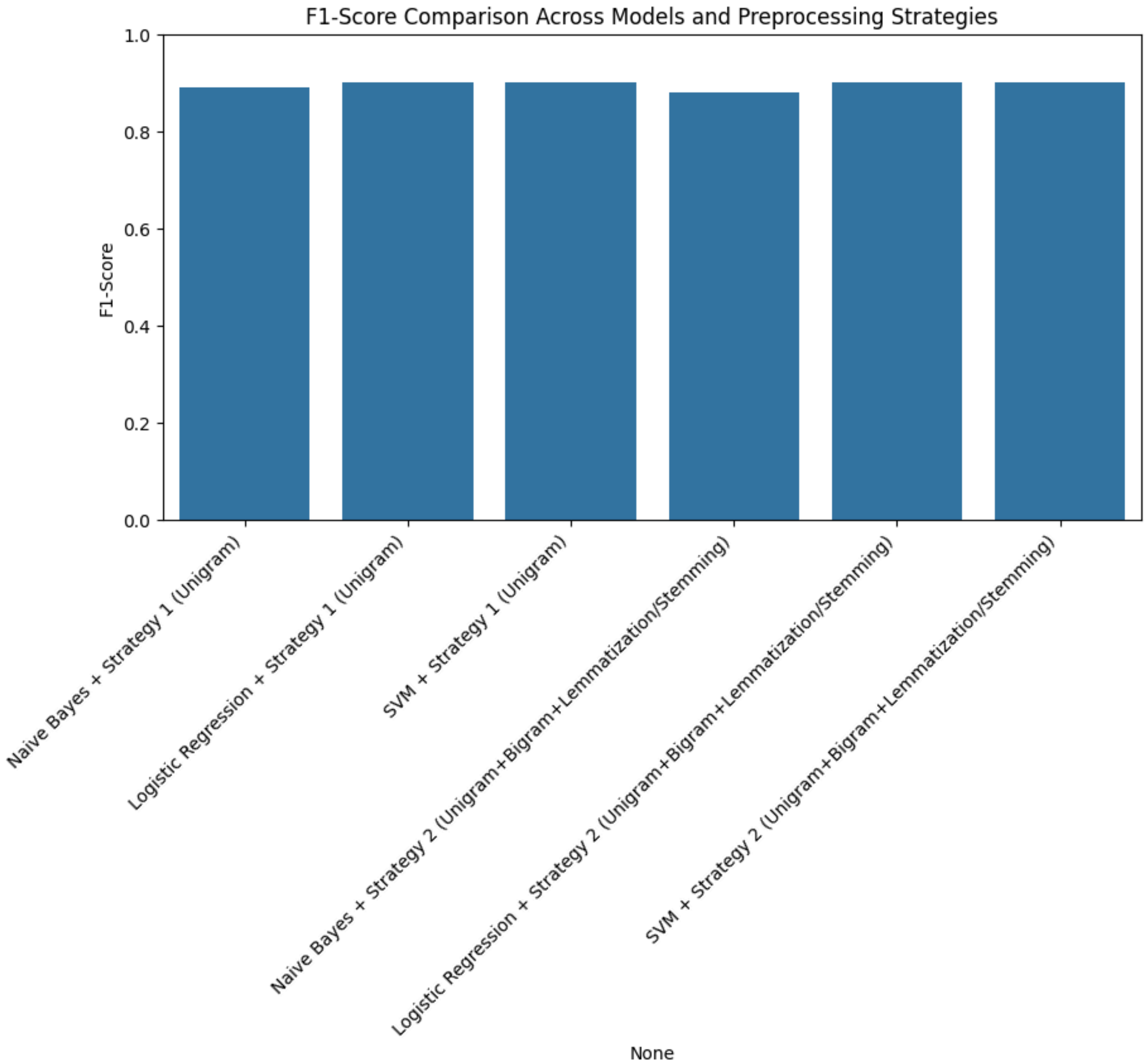
```
COMPARISON OF ML MODELS AND PREPROCESSING STRATEGIES
```

	Accuracy	Precision	Recall	F1-Score
Naive Bayes + Strategy 1 (Unigram)	0.8211	0.8177	0.9808	0.8918
Logistic Regression + Strategy 1 (Unigram)	0.8429	0.8497	0.9610	0.9020
SVM + Strategy 1 (Unigram)	0.8474	0.8771	0.9269	0.9013
Naive Bayes + Strategy 2 (Unigram+Bigram+Lemmatization/Stemming)	0.7998	0.7948	0.9891	0.8814
Logistic Regression + Strategy 2 (Unigram+Bigram+Lemmatization/Stemming)	0.8427	0.8556	0.9513	0.9009
SVM + Strategy 2 (Unigram+Bigram+Lemmatization/Stemming)	0.8494	0.8856	0.9183	0.9016




Precision Comparison Across Models and Preprocessing Strategies
Precision
1.0
0.8
0.6
0.4
0.2
0.0
Naive Bayes + Strategy 1 (Unigram)
Logistic Regression + Strategy 1 (Unigram)
SVM + Strategy 1 (Unigram)
Naive Bayes + Strategy 2 (Unigram+Bigram+Lemmatization/Stemming)
Logistic Regression + Strategy 2 (Unigram+Bigram+Lemmatization/Stemming)
SVM + Strategy 2 (Unigram+Bigram+Lemmatization/Stemming)
None

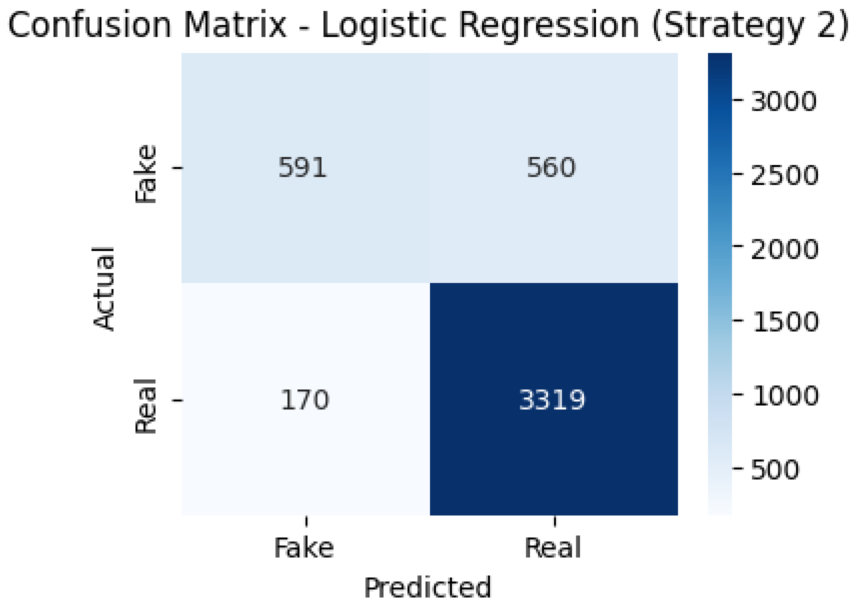

Recall Comparison Across Models and Preprocessing Strategies
Recall
1.0
0.8
0.6
0.4
0.2
0.0
Naive Bayes + Strategy 1 (Unigram)
Logistic Regression + Strategy 1 (Unigram)
SVM + Strategy 1 (Unigram)
Naive Bayes + Strategy 2 (Unigram+Bigram+Lemmatization/Stemming)
Logistic Regression + Strategy 2 (Unigram+Bigram+Lemmatization/Stemming)
SVM + Strategy 2 (Unigram+Bigram+Lemmatization/Stemming)
None



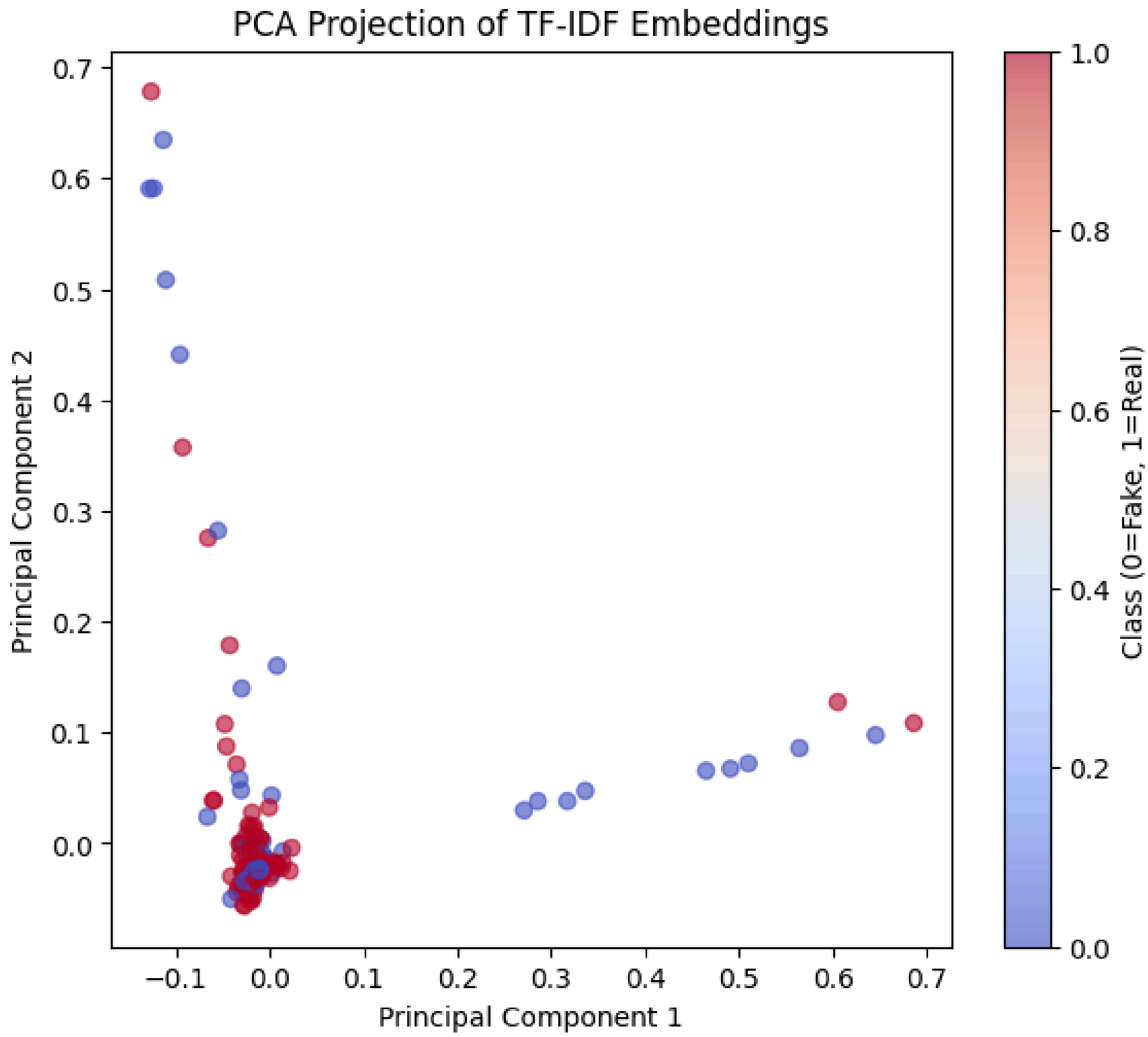
Comparison of Results

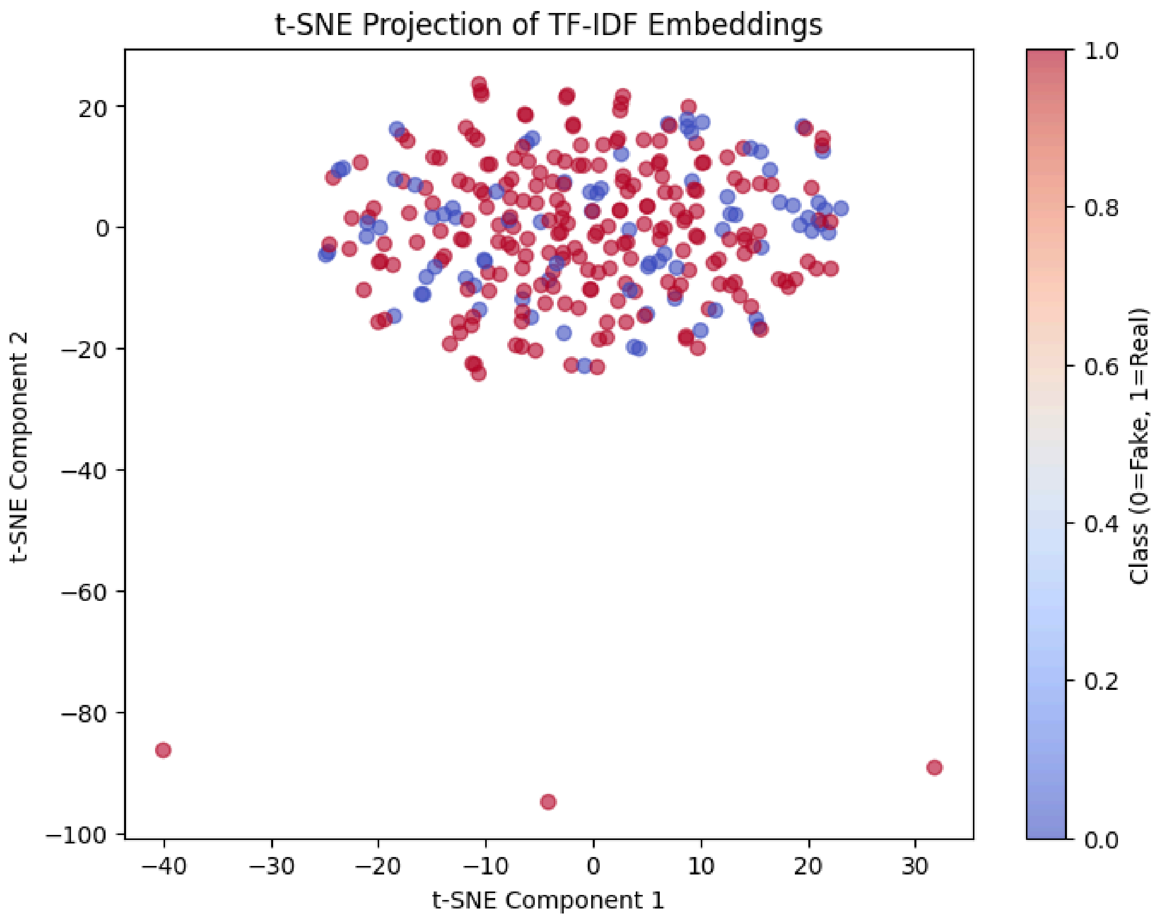
1. Comparison between Two Preprocessing Strategies:
- Strategy 1 Basic preprocessing: {(Lowercasing, Handling special characters, numbers & URLs, Stopword removal, Tokenization) + (unigrams)} generally performs slightly lower than Strategy 2 {(Lemmatization/Stemming) + (Unigrams+Bigrams)}, indicating that lemmatization and n-grams help capture more meaningful text features.

2. Comparison between Different Machine Learning Models:
- Logistic Regression and SVM generally achieve higher accuracy and F1-score compared to Naive Bayes, showing that linear models better separate real vs fake news based on TF-IDF features.
- Naive Bayes is still competitive and faster, but slightly less accurate on bigram features.




```
Cosine Similarity Matrix:
 [[1. 0. 0. 0. 0.]
 [0. 1. 0. 0. 0.]
 [0. 0. 1. 0. 0.]
 [0. 0. 0. 1. 0.]
 [0. 0. 0. 0. 1.]]
```




t-SNE Projection of TF-IDF Embeddings
t-SNE Component 1
t-SNE Component 2
Class (0=Fake, 1=Real)
20
0
−20
−40
−60
−80
−100
−40
−30
−20
−10
0
10
20
30
1.0
0.8
0.6
0.4
0.2
0.0