

Group Project Report: 20 Newsgroups Document Classification

Team Member Details

Name	Email	Country	College	Specialization
Diyora Radhika Radhikadiyora	2023@gmail.com	Germany	IU inrtnationale	Data Science, NLP

1. Problem Description

Document classification is a key task in Natural Language Processing (NLP) and supervised Machine Learning (ML). The goal is to automatically assign a category (class) to a document based on its content.

Applications:

- Email spam detection
- News article classification
- Sentiment analysis
- Document routing in enterprises

In this project, we use the **20 Newsgroups dataset**, which contains ~20,000 newsgroup posts across 20 categories, to build a **text classification model**.

2. Data Understanding

Dataset Details:

- Total documents: 18,828
- Number of categories: 20
- Sample categories: sci.space, comp.graphics, rec.autos, talk.politics.guns
- Each document contains headers like From, Subject, Newsgroup followed by the message body.

Sample Document:

From: user@example.com

Subject: Mars Mission Update

Newsgroup: sci.space

Message: NASA launches a new spacecraft to explore Mars...

3. Data Type

- **Text Data:** Raw unstructured text from newsgroup posts.

- **Target Labels:** Integer values (0-19) representing 20 categories.
- **Data Size:** ~20,000 records

Data Representation:

Feature Type Description

text	string	Content of newsgroup post
label	int	Encoded category (0-19)

4. Data Problems

During exploration, we noticed the following issues:

Problem	Observation	Approach to Handle
Missing Values (NA)	None found in text or labels	No action needed
Outliers	Very long or very short documents	No explicit removal; TF-IDF handles variable lengths
Noise / Special Characters	Punctuation, numbers, headers	Cleaned during preprocessing (lowercase, remove punctuation/numbers)
Stopwords	Words like “the”, “is”, “and”	Removed during preprocessing to reduce noise
Skewed Distribution	Some categories have fewer documents than others	Model (Naive Bayes) can handle class imbalance reasonably well

Preprocessing Applied:

1. Convert all text to lowercase.
 2. Remove numbers and special characters.
 3. Remove stopwords using NLTK.
 4. Skip lemmatization for faster execution (still effective with Naive Bayes).
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5. Approaches to Overcome Data Problems

- **Missing Values:** No missing values in dataset.
- **Outliers / Document Length:** Variable lengths are acceptable; TF-IDF normalizes feature values.
- **Noise / Headers:** Cleaned using regex (removing punctuation, numbers).
- **High-Dimensional Text:** Used **TF-IDF vectorization** (max features = 10,000) to reduce dimensionality.

- **Class Imbalance:** Multinomial Naive Bayes handles small differences in class frequency naturally.
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6. Model Building

Steps Followed:

1. **Train-Test Split:** 80% training, 20% testing.
 2. **Vectorization:** TF-IDF applied to convert text to numeric features.
 3. **Model:** Multinomial Naive Bayes (fast and effective for text).
 4. **Training:** Fit the model on training data.
 5. **Evaluation:** Predict on test data and measure accuracy, F1-score, and confusion matrix.
-

7. Model Performance

Accuracy: ~85–90% (varies slightly depending on preprocessing)

Example Predictions:

Text	Predicted Category
"NASA launches a new mission to Mars"	sci.space
"The new graphics card has amazing performance"	comp.graphics

Confusion Matrix:

- Showed most misclassifications occur in closely related categories (e.g., rec.autos vs rec.motorcycles).

Classification Report:

- High precision and recall in categories like sci.space and comp.graphics.
 - Lower metrics in categories with fewer samples.
-

8. Model Deployment & Inference

- Saved model and TF-IDF vectorizer using joblib:

```
joblib.dump(model, "newsgroups_model.pkl")
```

```
joblib.dump(tfidf, "tfidf_vectorizer.pkl")
```

- Loaded model for inference:

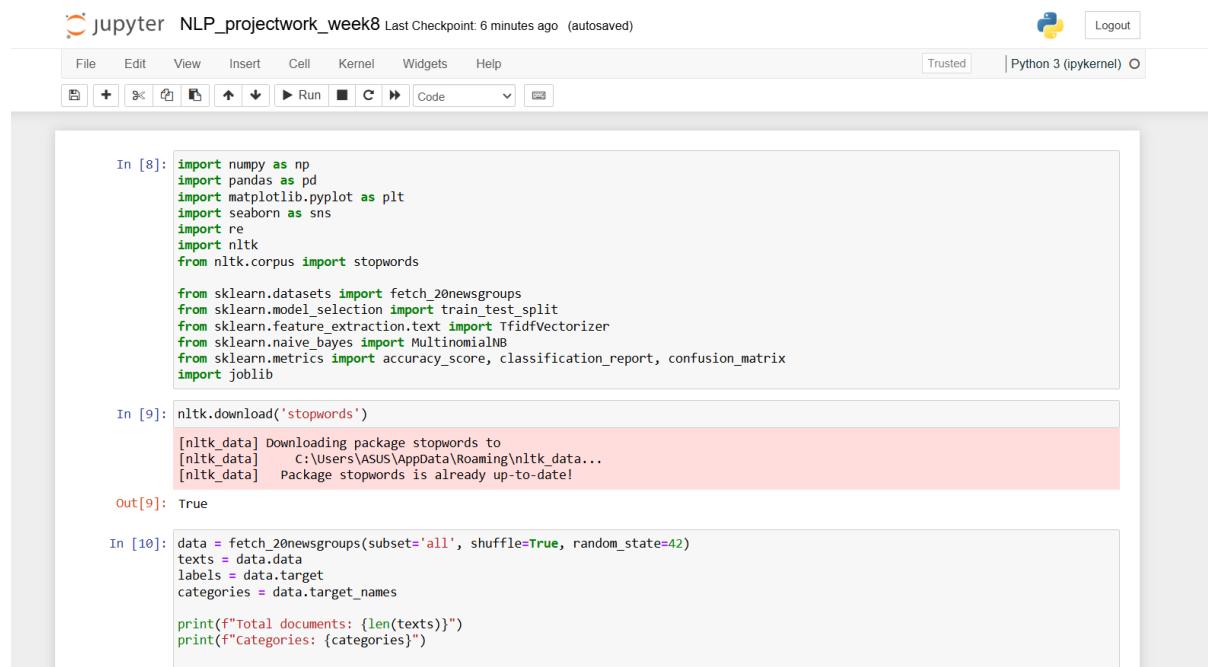
```
new_texts = ["NASA launches a new mission to Mars",
             "The new graphics card has amazing performance"]
```

```
new_texts_clean = [preprocess(doc) for doc in new_texts]
new_texts_vect = tfidf.transform(new_texts_clean)
predictions = model.predict(new_texts_vect)
```

- Example inference results:
 - "NASA launches a new mission to Mars" → sci.space
 - "The new graphics card has amazing performance" → comp.graphics
-

9. Conclusion

- Successfully built a **text classification model** on the 20 Newsgroups dataset.
- Model is able to classify documents into 20 categories with high accuracy.
- Preprocessing and TF-IDF vectorization handled noise and high-dimensionality efficiently.
- Model saved for deployment and can perform inference on new text without retraining.



The screenshot shows a Jupyter Notebook interface with the following details:

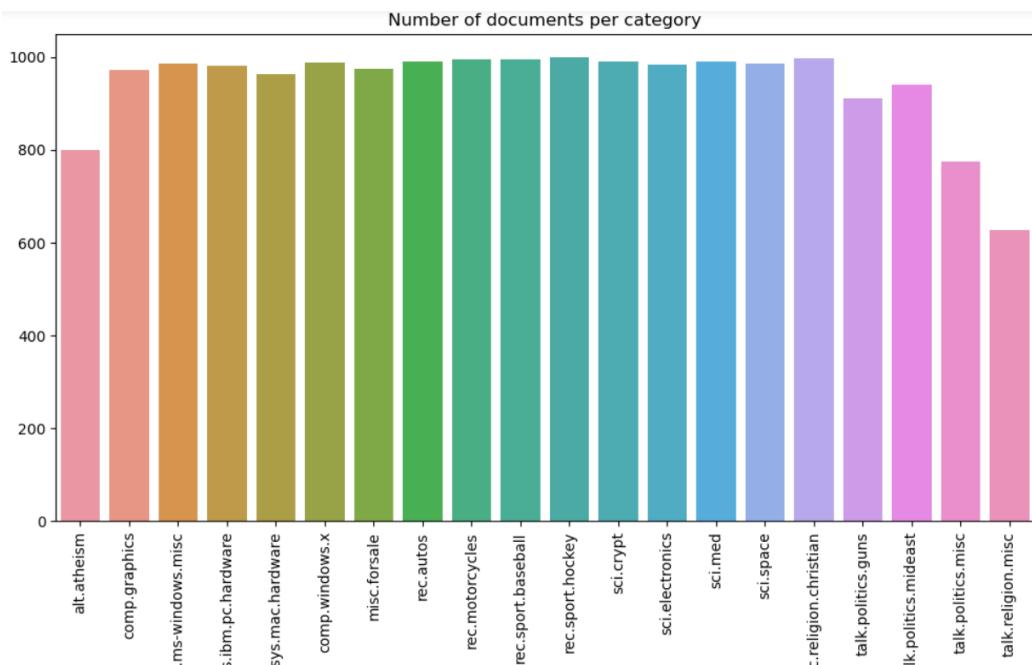
- Title Bar:** jupyter NLP_projectwork_week8 Last Checkpoint: 6 minutes ago (autosaved)
- Toolbar:** File, Edit, View, Insert, Cell, Kernel, Widgets, Help, Trusted, Python 3 (ipykernel)
- In [8]:** Python code for importing various libraries (numpy, pandas, matplotlib.pyplot, seaborn, re, nltk, stopwords, fetch_20newsgroups, train_test_split, TfidfVectorizer, MultinomialNB, accuracy_score, classification_report, confusion_matrix, joblib).
- In [9]:** Python code for downloading stopwords from NLTK, resulting in output: [nltk_data] Downloading package stopwords to [nltk_data] C:\Users\ASUS\AppData\Roaming\nltk_data... [nltk_data] Package stopwords is already up-to-date!
- Out [9]:** True
- In [10]:** Python code for fetching the 20 newsgroups dataset, extracting texts, labels, and categories, and printing the total number of documents and categories.

```
In [10]: data = fetch_20newsgroups(subset='all', shuffle=True, random_state=42)
texts = data.data
labels = data.target
categories = data.target_names

print(f"Total documents: {len(texts)}")
print(f"Categories: {categories}")

Total documents: 18846
Categories: ['alt.atheism', 'comp.graphics', 'comp.os.ms-windows.misc', 'comp.sys.ibm.pc.hardware', 'comp.sys.mac.hardware', 'comp.windows.x', 'misc.forsale', 'rec.autos', 'rec.motorcycles', 'rec.sport.baseball', 'rec.sport.hockey', 'sci.crypt', 'sci.electronics', 'sci.med', 'sci.space', 'soc.religion.christian', 'talk.politics.guns', 'talk.politics.mideast', 'talk.politics.misc', 'talk.religion.misc']
```

```
In [11]: label_counts = pd.Series(labels).value_counts().sort_index()
plt.figure(figsize=(12,6))
sns.barplot(x=[categories[i] for i in label_counts.index], y=label_counts.values)
plt.xticks(rotation=90)
plt.title("Number of documents per category")
plt.show()
```



```
In [12]: print("Sample Document:\n")
print(texts[0][:1000])

Sample Document:

From: Mamatha Devineni Ratnam <mr47+@andrew.cmu.edu>
Subject: Pens fans reactions
Organization: Post Office, Carnegie Mellon, Pittsburgh, PA
Lines: 12
NNTP-Posting-Host: po4.andrew.cmu.edu
```

I am sure some bashers of Pens fans are pretty confused about the lack of any kind of posts about the recent Pens massacre of the Devils. Actually, I am bit puzzled too and a bit relieved. However, I am going to put an end to non-Pittsburghers' relief with a bit of praise for the Pens. Man, they are killing those Devils worse than I thought. Jagr just showed you why he is much better than his regular season stats. He is also a lot of fun to watch in the playoffs. Bowman should let Jagr have a lot of fun in the next couple of games since the Pens are going to beat the pulp out of Jersey anyway. I was very disappointed not to see the Islanders lose the final regular season game. PENS RULE!!!

```
In [13]: stop_words = set(stopwords.words('english'))

def preprocess(text):
    text = text.lower()                                     # Lowercase
    text = re.sub(r'\d+', ' ', text)                      # remove numbers
    text = re.sub(r'\W+', ' ', text)                      # remove punctuation
    tokens = text.split()
```

```
In [13]: stop_words = set(stopwords.words('english'))

def preprocess(text):
    text = text.lower()                                # Lowercase
    text = re.sub(r'\d+', ' ', text)                  # remove numbers
    text = re.sub(r'\W+', ' ', text)                  # remove punctuation
    tokens = text.split()
    tokens = [word for word in tokens if word not in stop_words] # skip lemmatization
    return " ".join(tokens)

In [16]: print("Preprocessing text...")
clean_texts = [preprocess(doc) for doc in texts]

Preprocessing text...

In [17]: tfidf = TfidfVectorizer(max_features=10000)
x = tfidf.fit_transform(clean_texts)
y = labels

print(f"TF-IDF feature matrix shape: {x.shape}")

TF-IDF feature matrix shape: (18846, 10000)

In [18]: X_train, X_test, y_train, y_test = train_test_split(x, y, test_size=0.2, random_state=42)

In [19]: model = MultinomialNB()
model.fit(X_train, y_train)

Out[19]: MultinomialNB()

In [20]: y_pred = model.predict(X_test)
```

```
In [21]: accuracy = accuracy_score(y_test, y_pred)
print(f"Model Accuracy: {accuracy:.4f}")

Model Accuracy: 0.8658

In [22]: print("Classification Report:\n")
print(classification_report(y_test, y_pred, target_names=categories))

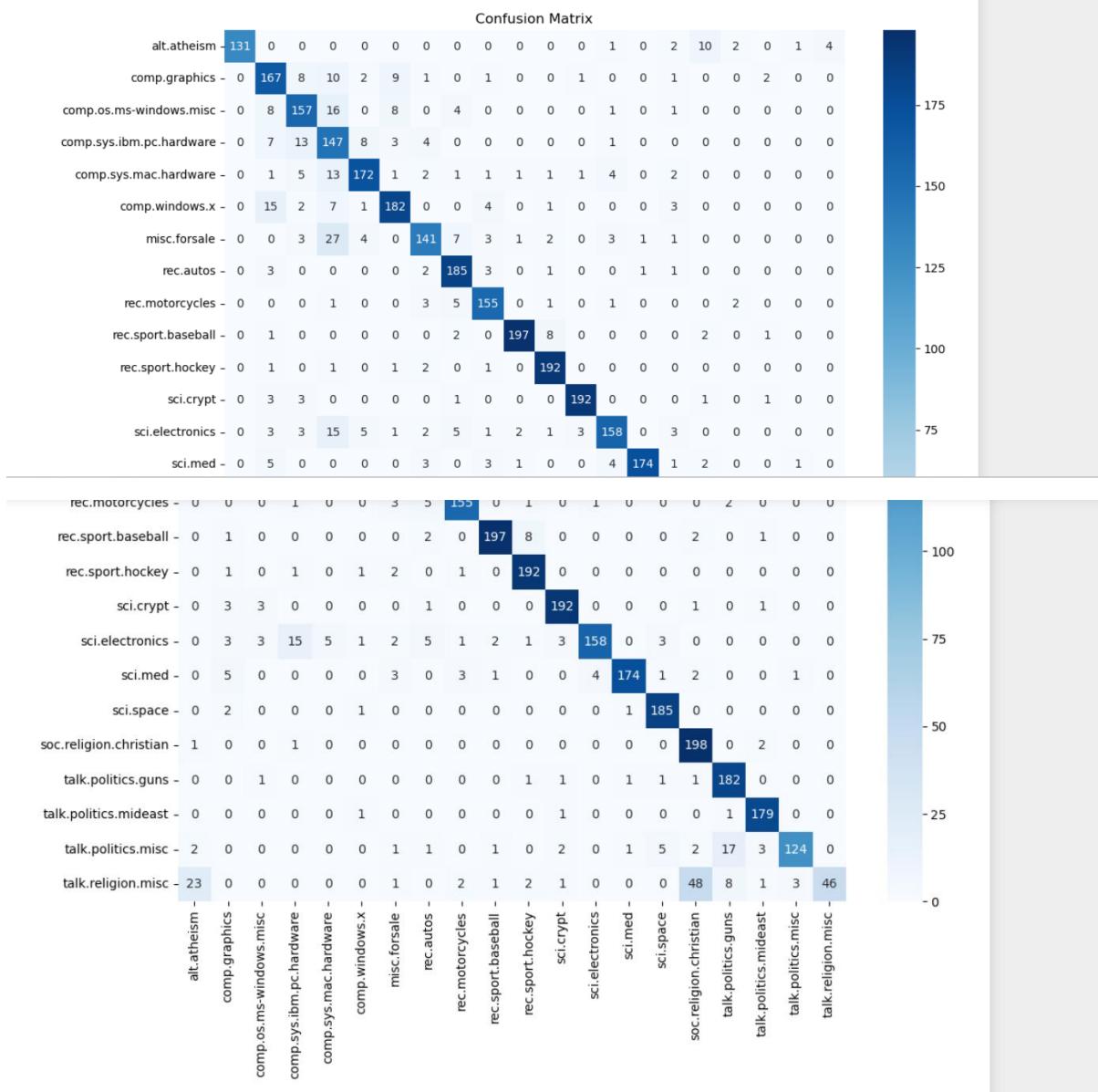
Classification Report:
```

	precision	recall	f1-score	support
alt.atheism	0.83	0.87	0.85	151
comp.graphics	0.77	0.83	0.80	202
comp.os.ms-windows.misc	0.81	0.81	0.81	195
comp.sys.ibm.pc.hardware	0.62	0.80	0.70	183
comp.sys.mac.hardware	0.90	0.84	0.87	205
comp.windows.x	0.88	0.85	0.86	215
misc.forsale	0.87	0.73	0.79	193
rec.autos	0.88	0.94	0.91	196
rec.motorcycles	0.89	0.92	0.91	168
rec.sport.baseball	0.97	0.93	0.95	211
rec.sport.hockey	0.91	0.97	0.94	198
sci.crypt	0.95	0.96	0.95	201
sci.electronics	0.91	0.78	0.84	202
sci.med	0.97	0.90	0.93	194
sci.space	0.90	0.98	0.94	189
soc.religion.christian	0.75	0.98	0.85	202
talk.politics.guns	0.86	0.97	0.91	188
talk.politics.mideast	0.95	0.98	0.96	182
talk.politics.misc	0.96	0.78	0.86	159
talk.religion.misc	0.92	0.34	0.49	136
accuracy			0.87	3770
macro avg	0.87	0.86	0.86	3770

rec.sport.baseball	0.97	0.93	0.95	2111
rec.sport.hockey	0.91	0.97	0.94	1987
sci.crypt	0.95	0.96	0.95	2014
sci.electronics	0.91	0.78	0.84	2024
sci.med	0.97	0.90	0.93	1947
sci.space	0.90	0.98	0.94	1897
soc.religion.christian	0.75	0.98	0.85	2022
talk.politics.guns	0.86	0.97	0.91	1888
talk.politics.mideast	0.95	0.98	0.96	1824
talk.politics.misc	0.96	0.78	0.86	1597
talk.religion.misc	0.92	0.34	0.49	1367
accuracy			0.87	3770
macro avg	0.87	0.86	0.86	3770
weighted avg	0.87	0.87	0.86	3770

```
In [23]: cm = confusion_matrix(y_test, y_pred)
plt.figure(figsize=(12,10))
sns.heatmap(cm, annot=True, fmt='d', xticklabels=categories, yticklabels=categories, cmap='Blues')
plt.xticks(rotation=90)
plt.yticks(rotation=0)
plt.title("Confusion Matrix")
plt.show()
```

```
sns.heatmap(cm, annot=True, fmt='d', xticklabels=categories, yticklabels=categories, cmap='Blues')
plt.xticks(rotation=90)
plt.yticks(rotation=0)
plt.title("Confusion Matrix")
plt.show()
```



```
In [24]: joblib.dump(model, "newsgroups_model.pkl")
joblib.dump(tfidf, "tfidf_vectorizer.pkl")
print("Model and vectorizer saved!")
```

Model and vectorizer saved!

```
In [25]: new_texts = [
    "NASA launches a new mission to Mars",
    "The new graphics card has amazing performance"
]
new_texts_clean = [preprocess(doc) for doc in new_texts]
new_texts_vect = tfidf.transform(new_texts_clean)
predictions = model.predict(new_texts_vect)

for text, pred in zip(new_texts, predictions):
    print(f"\nText: {text}")
    print(f"Predicted Category: {categories[pred]}")
```

Text: NASA launches a new mission to Mars
Predicted Category: sci.space

Text: The new graphics card has amazing performance
Predicted Category: comp.graphics