NATIONAL UNIVERSITY OF MODERN LANGUAGES ISLAMABAD

Natural Language Processing (Lab)

Open Ended Lab

Submitted to
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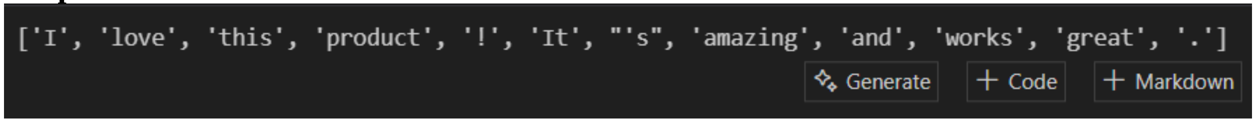
Question # 01

Task 1: Tokenization

Tokenize the sentence "I love this product! It's amazing and works great." using NLTK.

Output Screenshot:



```
['I', 'love', 'this', 'product', '!', 'It', "'s", 'amazing', 'and', 'works', 'great', '.']
```

Task 2: Morphemes in the Word

Manually break down the word 'unhappiness' into morphemes for linguistic analysis.

Explanation:

Prefix: 'un' means 'not'

Root: 'happy' means 'feeling of joy'

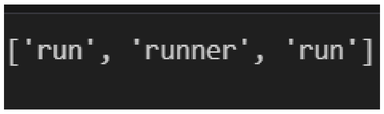
Suffix: 'ness' turns adjective to noun, meaning 'state of'.

So, 'unhappiness' means the state of not being happy.

Task 3: Stemming

Use Porter Stemmer from NLTK to stem the words: ['running', 'runner', 'runs'].

Output Screenshot:

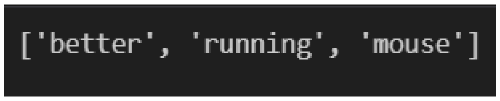


```
['run', 'runner', 'run']
```

Task 4: Lemmatization

Lemmatize the words ['better', 'running', 'mice'] using NLTK or spaCy.

Output Screenshot:



```
['better', 'running', 'mouse']
```

Task 5: Overstemming

Explain overstemming with an example of how it affects text analysis.

Explanation:

Overstemming is when words with different meanings are incorrectly reduced to the same root.

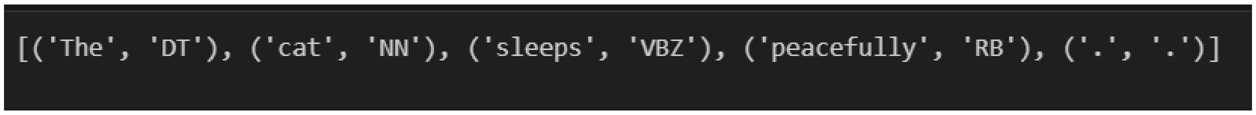
Example: 'organization' and 'organize' both stemmed to 'organ'.

This can reduce model accuracy in context-sensitive tasks.

Task 6: Part-of-Speech Tagging

Perform POS tagging on the sentence 'The cat sleeps peacefully.' using NLTK.

Output Screenshot:

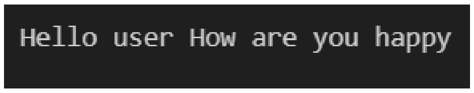


```
[('The', 'DT'), ('cat', 'NN'), ('sleeps', 'VBZ'), ('peacefully', 'RB'), ('.', '.')]
```

Task 7: Filter Out Non-Alphabetic Characters

Filter out non-alphabetic characters from the sentence: 'Hello @user! How are you? 123 #happy'.

Output Screenshot:

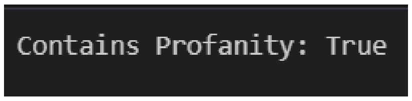


```
Hello user How are you happy
```

Task 8: Check for Profanity/Offensive Language

Detect offensive language in 'This is a great day, damn it!' using a simple list-based profanity filter.

Output Screenshot:

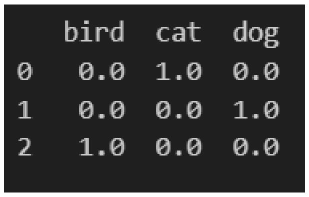


```
Contains Profanity: True
```

Task 9: One Hot Encoding

Perform one-hot encoding on the labels: ['cat', 'dog', 'bird'] using scikit-learn.

Output Screenshot:

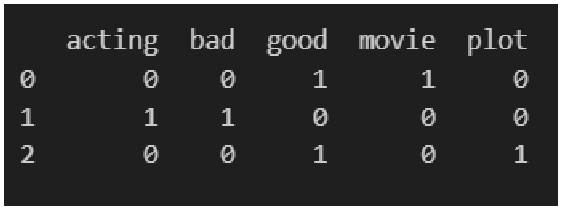


```
   bird  cat  dog
0   0.0  1.0  0.0
1   0.0  0.0  1.0
2   1.0  0.0  0.0
```

Task 10: Bag of Words

Use Bag of Words to vectorize movie reviews: ['good movie', 'bad acting', 'good plot'].

Output Screenshot:

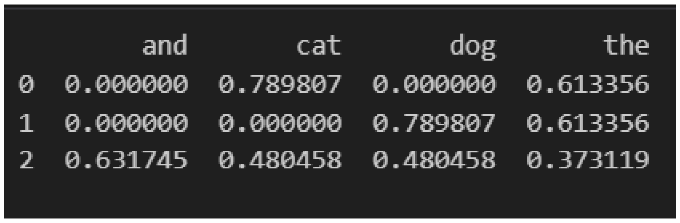


```
   acting  bad  good  movie  plot
0       0    0     1      1     0
1       1    1     0      0     0
2       0    0     1      0     1
```

Task 11: TF-IDF

Compute TF-IDF scores for documents: ['the cat', 'the dog', 'the cat and dog'].

Output Screenshot:

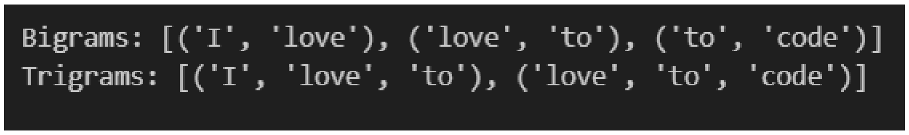


```
        and       cat       dog       the
0  0.000000  0.789807  0.000000  0.613356
1  0.000000  0.000000  0.789807  0.613356
2  0.631745  0.480458  0.480458  0.373119
```

Task 12: N-Grams

Extract bi-grams and tri-grams from the sentence: 'I love to code' using NLTK.

Output Screenshot:



```
Bigrams: [('I', 'love'), ('love', 'to'), ('to', 'code')]
Trigrams: [('I', 'love', 'to'), ('love', 'to', 'code')]
```

<u>Question # 02</u>

Description:

Task 1: Tokenization

Split the input text into individual words (tokens) while converting to lowercase and removing punctuation. This prepares the text for n-gram generation.

Task 2: N-gram Generation

Create both bi-grams (2-word sequences) and tri-grams (3-word sequences) from the tokenized text to identify meaningful word combinations.

Task 3: Stop Word Filtering

Remove n-grams that contain common stop words (like "the", "and") using NLTK's predefined list to focus on content-bearing phrases.

Task 4: Frequency Computation

Count how often each filtered n-gram appears in the text using Python's Counter for efficient frequency analysis.

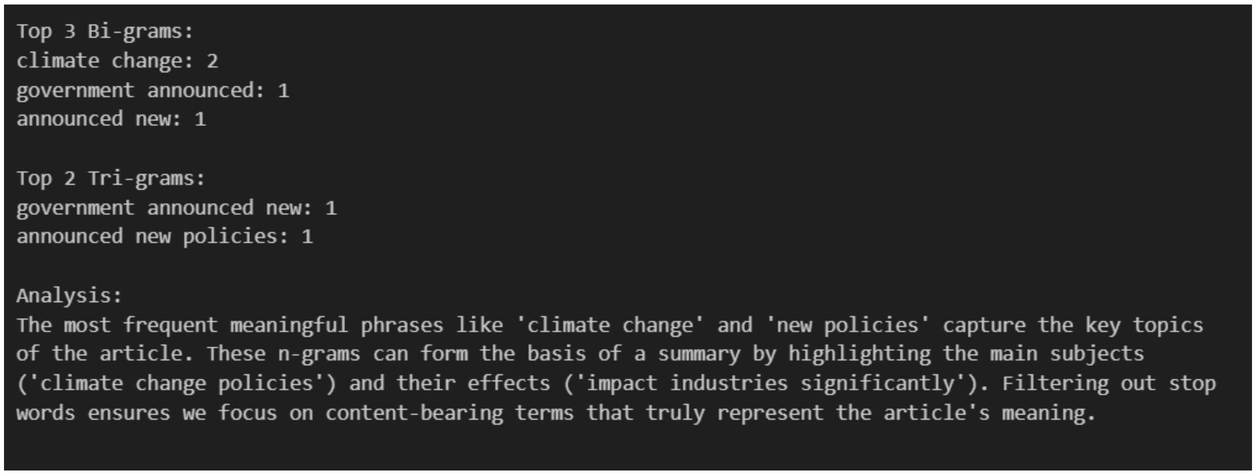
Task 5: Ranking N-grams

Sort the n-grams by their frequency and select the top 3 bi-grams and top 2 tri-grams to identify the most significant phrases.

Task 6: Summary Analysis

Explain how the selected high-frequency n-grams capture key concepts that could form the basis of a concise text summary.

Output Screenshot:



```
Top 3 Bi-grams:
climate change: 2
government announced: 1
announced new: 1

Top 2 Tri-grams:
government announced new: 1
announced new policies: 1

Analysis:
The most frequent meaningful phrases like 'climate change' and 'new policies' capture the key topics
of the article. These n-grams can form the basis of a summary by highlighting the main subjects
('climate change policies') and their effects ('impact industries significantly'). Filtering out stop
words ensures we focus on content-bearing terms that truly represent the article's meaning.
```

N-grams contribute to summarization by identifying key phrases, ranking sentences, reducing redundancy, and improving coherence. Filtering refines their impact by removing noise, but careful tuning is needed to balance informativeness and readability. The best approach depends on the domain, summarization method (extractive/abstractive), and desired summary length.

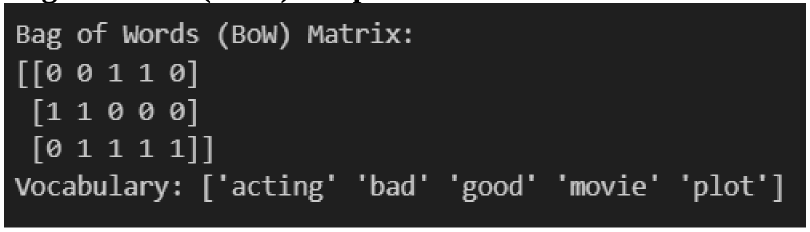
Question # 03

Description:

Bag of Words (BoW) simply counts word frequencies, treating all terms equally. TF-IDF, however, adjusts weights based on term importance, reducing the impact of common words (like "bad") while emphasizing rare, meaningful terms. For classification, TF-IDF is superior as it better distinguishes key terms like "acting" from overused ones like "bad."

Output Analysis

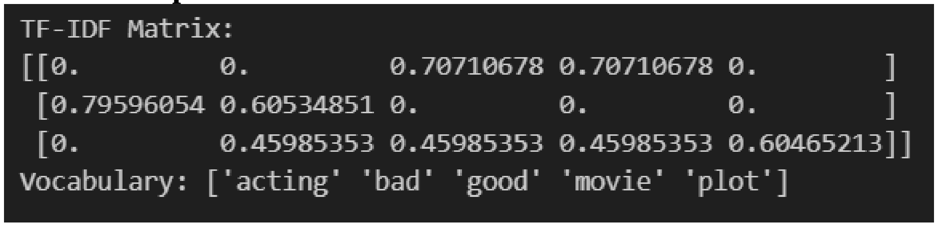
1. **Bag of Words (BoW) Output:**



```
Bag of Words (BoW) Matrix:
[[0 0 1 1 0]
 [1 1 0 0 0]
 [0 1 1 1 1]]
Vocabulary: ['acting' 'bad' 'good' 'movie' 'plot']
```

- "bad" appears twice (once in "bad acting" and once in "good plot bad movie").
- Limitation: BoW treats all words equally, ignoring term importance.

2. **TF-IDF Output:**



```
TF-IDF Matrix:
[[0.         0.         0.70710678 0.70710678 0.        ]
 [0.79596054 0.60534851 0.         0.         0.        ]
 [0.         0.45985353 0.45985353 0.45985353 0.60465213]]
Vocabulary: ['acting' 'bad' 'good' 'movie' 'plot']
```

- "bad" has a higher weight (0.707) in "bad acting" than in "good plot bad movie" (0.408).
- Reason: TF-IDF penalizes frequent terms (like "bad" appearing twice) while boosting rare, discriminative terms.

Justification: Which Method is Better for Classification?

✅ **TF-IDF is preferable** because:

1. It **downweights common terms** (e.g., "bad" in multiple docs) while **emphasizing discriminative terms** (e.g., "acting" appears only once).
2. It better captures **term importance** for classification by considering **document frequency (IDF)**.

❌ **BoW is less effective** since it treats all words equally, potentially overemphasizing frequent but less meaningful terms.