PROBABILITY N-GRAM

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EX.NO.: 10

To implement bigram modeling on a given corpus (Berkeley restaurant project corpus file) and perform the following tasks:

- 1. Extract text from the corpus file.
- 2. Generate all possible bigrams from the text.
- 3. Apply **Add-One Smoothing** and calculate the probabilities of all bigrams.
- 4. Query and print the probability of a given random bigram.
- 5. Implement and apply **Kneser-Nev Smoothing** for the bigram model.
- 6. Display the probability matrices for both smoothing methods.

PROCEDURE:

- 1. Read the Text Corpus:
 - a. Use the read file() function to load the corpus from the specified text file and convert it to lowercase for consistency.
- 2. Tokenize the Text:
 - a. Use NLTK's word tokenize() function to split the text into individual tokens (words).
- 3. Generate Unigrams and Bigrams:
 - a. Extract unigrams (single tokens) directly from the tokenized text.
 - b. Use the ngrams() function from NLTK to generate all bigrams from the tokenized text.
- 4. Calculate Unigram and Bigram Counts:
 - a. Count the occurrences of each unigram using Counter.
 - b. Similarly, count the occurrences of each bigram using Counter.
- 5. Add-One Smoothing:
 - a. Implement Add-One smoothing to adjust the probabilities of bigrams, avoiding zero probabilities for unseen bigrams.
 - b. Use the formula: $P(w2 | w1) = C(w1, w2) + 1C(w1) + |V|P(w 2|w 1) = \frac{c(w1, w2)}{+} + \frac{c(w1, w2)}$ 1\} $\{ \text{V} = C(w_1) + |\text{V}| \} P(w_2|w_1) = C(w_1) + |V| C(w_1, w_2) + 1 \text{ where } |V| |\text{V}| |V| \text{ is } |V| = C(w_1, w_2) + 1 \text{ where } |V| = C(w_1, w_2) + 1 \text{ where } |V| = C(w_1, w_2) + 1 \text{ where } |V| = C(w_1, w_2) + 1 \text{ where } |V| = C(w_1, w_2) + 1 \text{ where } |V| = C(w_1, w_2) + 1 \text{ where } |V| = C(w_1, w_2) + 1 \text{ where } |V| = C(w_1, w_2) + 1 \text{ where } |V| = C(w_1, w_2) + 1 \text{ where } |V| = C(w_1, w_2) + 1 \text{ where } |V| = C(w_1, w_2) + 1 \text{ where } |V| = C(w_1, w_2) + 1 \text{ where } |V| = C(w_1, w_2) + 1 \text{ where } |V| = C(w_1, w_2) + 1 \text{ where } |V| = C(w_1, w_2) + 1 \text{ where } |V| = C(w_1, w_2) + 1 \text{ where } |V| = C(w_1, w_2) + 1 \text{ where } |V| = C(w_1, w_2) + 1 \text{ where } |V| = C(w_1, w_2) + 1 \text{ where } |V| = C(w_1, w_2) + 1 \text{ where } |V| = C(w_1, w_2) + 1 \text{ where } |V| = C(w_1, w_2) + 1 \text{ where } |V| = C(w_1, w_2) + 1 \text{ where } |V| = C(w_1, w_2) + 1 \text{ where } |V| = C(w_1, w_2) + 1 \text{ where } |V| = C(w_1, w_2) + 1 \text{ where } |V| = C(w_1, w_2) + 1 \text{ where } |V| = C(w_1, w_2) + 1 \text{ where } |V| = C(w_1, w_2) + 1 \text{ where } |V| = C(w_1, w_2) + 1 \text{ where } |V| = C(w_1, w_2) + 1 \text{ where } |V| = C(w_1, w_2) + 1 \text{ where } |V| = C(w_1, w_2) + 1 \text{ where } |V| = C(w_1, w_2) + 1 \text{ where } |V| = C(w_1, w_2) + 1 \text{ where } |V| = C(w_1, w_2) + 1 \text{ where } |V| = C(w_1, w_2) + 1 \text{ where } |V| = C(w_1, w_2) + 1 \text{ where } |V| = C(w_1, w_2) + 1 \text{ where } |V| = C(w_1, w_2) + 1 \text{ where } |V| = C(w_1, w_2) + 1 \text{ where } |V| = C(w_1, w_2) + 1 \text{ where } |V| = C(w_1, w_2) + 1 \text{ where } |V| = C(w_1, w_2) + 1 \text{ where } |V| = C(w_1, w_2) + 1 \text{ where } |V| = C(w_1, w_2) + 1 \text{ where } |V| = C(w_1, w_2) + 1 \text{ where } |V| = C(w_1, w_2) + 1 \text{ where } |V| = C(w_1, w_2) + 1 \text{ where } |V| = C(w_1, w_2) + 1 \text{ where } |V| = C(w_1, w_2) + 1 \text{ where } |V| = C(w_1, w_2) + 1 \text{ where } |V| = C(w_1, w_2) + 1 \text{ where } |V| = C(w_1, w_2) + 1 \text{ where } |V| = C(w_1, w_2) + 1 \text{ where } |V| = C(w_1, w_2) + 1 \text{ where } |V| = C(w_1, w_2) + 1 \text{ where } |V| = C(w_1, w_2) + 1 \text{ where } |V| = C(w_1, w_2) + 1 \text$ the vocabulary size.
- 6. Generate Probability Matrix for Add-One Smoothing:
 - a. Use the generate bigram matrix() function to construct a matrix where rows and columns represent vocabulary words, and each cell shows the smoothed probability of the bigram.
- 7. Kneser-Ney Smoothing:
 - a. Implement Kneser-Ney smoothing, which redistributes probability mass to account for lower-order n-gram probabilities.
 - b. Use the formula: PKN(w2 | w1) = max(C(w1, w1)) = max $w^2-d_0/C(w^1)+d\cdot Continuations(w^2) | Vocabulary | P \{ (kN) \} (w^2|w^1) = (w^2-d_0)/C(w^1)+d\cdot Continuations(w^2) | Vocabulary | P \{ (kN) \} (w^2|w^1) = (kN) \}$ $\max(\det\{C(w1, w2)\} - d, 0) / \det\{C(w1)\} + d \cdot d$ $\frac{|\text{Continuations}(w 2)|}{|\text{Vocabulary}|} PKN(w2|w1) = \max(C(w1, w2)|)$ w^2)-d,0)/C(w^1)+d·|Vocabulary||Continuations(w^2)| where ddd is the discount factor.
- 8. Generate Probability Matrix for Kneser-Ney Smoothing:
 - a. Use the generate bigram matrix() function to display the Kneser-Ney smoothed bigram probabilities in a matrix format.
- 9. Query for a Random Bigram:
 - a. Accept or define a random bigram input (e.g., ('restaurant', 'berkeley')).
 - b. Retrieve and print the probability of the bigram for both Add-One and Kneser-Ney smoothing methods.
- 10. Output Results:
 - a. Display the bigram probability matrices for both Add-One and Kneser-Ney smoothing.
 - b. Print the queried bigram probabilities with clear labels.

CODE AND OUTPUT

from nltk.util import ngrams

```
def read file(file path):
   with open(file path, 'r') as file:
        return file.read().lower()
def add one smoothing(bigrams, unigram counts, vocabulary size):
   bigram counts = Counter(bigrams)
   smoothed probabilities = {}
   for bigram in bigram counts:
        smoothed probabilities[bigram] = (bigram counts[bigram] + 1) /
(unigram counts[bigram[0]] + vocabulary size)
   return smoothed probabilities
def generate_bigram_count_matrix(tokens, bigrams, vocabulary_size):
   vocab = sorted(set(tokens))
   unigram counts = Counter(tokens)
   bigram counts = Counter(bigrams)
   bigram count matrix = pd.DataFrame(0, index=vocab, columns=vocab, dtype=int)
   for w1 in vocab:
       for w2 in vocab:
            bigram count matrix.loc[w1, w2] = bigram counts[(w1, w2)] + 1 # Add-One
   return bigram count matrix
def generate bigram probability matrix(tokens, smoothed probabilities):
   vocab = sorted(set(tokens))
   bigram matrix = pd.DataFrame(0, index=vocab, columns=vocab, dtype=float)
   for (w1, w2), prob in smoothed probabilities.items():
       bigram matrix.loc[w1, w2] = prob
   return bigram matrix
def main():
   nltk.download('punkt')
```

```
file path = 'corpus.txt' # Replace with your file path
    text = read file(file path)
   tokens = nltk.word tokenize(text)
   unigrams = tokens
   bigrams = list(ngrams(tokens, 2))
   unigram counts = Counter(unigrams)
   vocabulary size = len(unigram counts)
   add one probs = add one smoothing(bigrams, unigram counts, vocabulary size)
   bigram count matrix = generate bigram count matrix(tokens, bigrams,
vocabulary size)
   bigram probability matrix = generate bigram probability matrix(tokens,
add one probs)
   print("\nBigram Probability Matrix with Add-One Smoothing:")
   print(bigram probability matrix.round(4))
   print("Bigram Count Matrix with Add-One Smoothing:")
   print(bigram count matrix)
   def get bigram probability(smoothed probabilities, bigram):
        return smoothed probabilities.get(bigram, "Bigram not found")
   random bigram = ('spend', 'money') # example input bigram
   probability = get bigram probability(add one probs, random bigram)
   print(f"Probability of the bigram {random bigram}: {probability}")
   main()
```

```
Bigram Probability Matrix with Add-One Smoothing:
          chinese delicious eat favorite
                                                         for
                                                 food
           0.0000
                     0.0000
                             0.0000
                                       0.0000 0.2963
                                                      0.0000
chinese
                                                              0.0000
delicious
           0.1053
                     0.0000 0.0000
                                       0.0000 0.1053
                                                      0.0000
                                                              0.0000
                     0.0000 0.0000
                                       0.0000 0.0769 0.0000
eat
           0.2308
                                                              0.0000
favorite
           0.0000
                     0.0000 0.0000
                                       0.0000 0.0000 0.0000 0.0000
                     0.0000 0.1071
                                      0.0000 0.0000 0.1071 0.0714
food
           0.0000
                     0.0000 0.0000
                                       0.0000 0.0000 0.0000 0.0000
for
           0.0000
           0.0000
                     0.0000
                             0.0000
                                       0.0000
                                              0.0000
                                                      0.0000
                                                              0.0000
           0.0000
                     0.1429 0.0000
                                       0.0000 0.0000 0.0000
                                                              0.0000
1unch
           0.1111
                     0.0000 0.0741
                                      0.0000 0.0000 0.0000 0.1111
meal
           0.0000
                     0.0000 0.0000 0.0000 0.0000 0.0000
                     0.0000 0.0000
                                      0.0000 0.0000 0.0000 0.0909
           0.0000
money
           0.0000
                     0.0000 0.0000
                                       0.1111 0.0000 0.0000
                                                              0.0000
my
           0.1000
                      0.0000
                             0.0000
                                       0.0000
                                               0.1000
                                                      0.0000
           0.0000
                     0.0000 0.0000
spend
                                       0.0000 0.0000 0.0000
                                                              0.0000
           0.0000
                     0.0000 0.0000
                                       0.0000 0.1111 0.0000 0.0000
tasty
           0.0000
                     0.0000 0.2800
                                       0.0000 0.0000 0.0000 0.0000
                                       0.0000 0.0000 0.0000 0.0000
           0.0909
                     0.0000 0.0000
want
                  lunch
                           meal
                                  money
                                                                 tasty
                                             my
                                                         spend
chinese
          0.0000 0.1481 0.0000 0.0000 0.0000 0.0000 0.0000 0.0000
delicious 0.0000 0.0000 0.0000 0.0000 0.0000 0.0000 0.0000
          0.0000 0.1538 0.0000 0.0000 0.0000 0.0000 0.0000 0.0000
tasty
to
want
Probability of the bigram ('spend', 'money'): 0.2727272727272727
Output is truncated. View as a <u>scrollable element</u> or open in a <u>text editor</u>. Adjust cell output <u>settings</u>...
[nltk_data] Downloading package punkt to
[nltk_data]
              C:\Users\Hema\AppData\Roaming\nltk_data...
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```