Experiment No.5
Implement N-Gram model for the given text input.
Date of Performance:
Date of Submission:

Aim: Implement N-Gram model for the given text input.
Objective: To study and implement N-gram Language Model.
Theory:
A language model supports predicting the completion of a sentence.
Eg:

- Please turn off your cell _____
- Your program does not ______

Predictive text input systems can guess what you are typing and give choices on how to complete it.

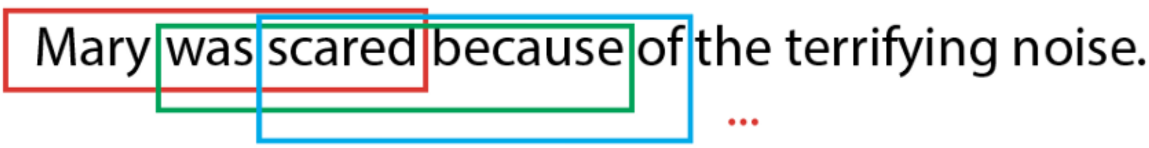
N-gram Models:
Estimate probability of each word given prior context.
P(phone | Please turn off your cell)

- Number of parameters required grows exponentially with the number of words of prior context.
- An N-gram model uses only N1 words of prior context.
    - Unigram: P(phone)
    - Bigram: P(phone | cell)
    - Trigram: P(phone | your cell)

- The Markov assumption is the presumption that the future behavior of a dynamical system only depends on its recent history. In particular, in a kth-order Markov model, the next state only depends on the k most recent states, therefore an N-gram model is a (N1)-order Markov model.

N-grams: a contiguous sequence of n tokens from a given piece of text

Fig. Example of Trigrams in a sentence



Code:

```
import nltk
import re
import pprint
import string
from nltk import word_tokenize, sent_tokenize
from nltk.util import ngrams
from nltk.corpus import stopwords
# Include additional punctuation marks for processing
```

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string.punctuation += '“”–’‘—'
string.punctuation = string.punctuation.replace('.', '')
# Load and preprocess the data
file = open('./dataset.txt', encoding='utf8').read()
file_nl_removed = " ".join(file.splitlines())  # Remove newlines and join lines
file_p = "".join([char for char in file_nl_removed if char not in string.punctuation])
### Statistics of the Data
sents = nltk.sent_tokenize(file_p)
print("The number of sentences is", len(sents))
words = nltk.word_tokenize(file_p)
print("The number of tokens is", len(words))
average_tokens = round(len(words) / len(sents))
print("The average number of tokens per sentence is", average_tokens)
unique_tokens = set(words)
print("The number of unique tokens are", len(unique_tokens))
### Building the N-Gram Model
stop_words = set(stopwords.words('english'))
unigram = []
bigram = []
trigram = []
fourgram = []
tokenized_text = []
# Process each sentence for n-grams
for sentence in sents:
    sequence = word_tokenize(sentence.lower())
    unigram.extend(word for word in sequence if word not in ('.',))  # Skip periods
    tokenized_text.append(sequence)
    bigram.extend(list(ngrams(sequence, 2)))
    trigram.extend(list(ngrams(sequence, 3)))
    fourgram.extend(list(ngrams(sequence, 4)))
# Function to remove n-grams containing only stopwords
def removal(x):
    return [pair for pair in x if any(word not in stop_words for word in pair)]
# Remove stopwords from n-grams
bigram = removal(bigram)
trigram = removal(trigram)
fourgram = removal(fourgram)
# Frequency distribution of n-grams
freq_bi = nltk.FreqDist(bigram)
freq_tri = nltk.FreqDist(trigram)
freq_four = nltk.FreqDist(fourgram)
print("Most common n-grams without stopword removal and without add-1 smoothing: \n")
print("Most common bigrams: ", freq_bi.most_common(5))
print("\nMost common trigrams: ", freq_tri.most_common(5))
print("\nMost common fourgrams: ", freq_four.most_common(5))
### Print 10 Unigrams and Bigrams after removing stopwords
unigram_sw_removed = [p for p in unigram if p not in stop_words]
fdist = nltk.FreqDist(unigram_sw_removed)
print("Most common unigrams: ", fdist.most_common(10))
```

```
bigram_sw_removed = list(ngrams(unigram_sw_removed, 2))
fdist = nltk.FreqDist(bigram_sw_removed)
print("\nMost common bigrams: ", fdist.most_common(10))
### Add-1 smoothing
ngrams_all = {1: [], 2: [], 3: [], 4: []}
ngrams_voc = {1: set(), 2: set(), 3: set(), 4: set()}
for i in range(4):
    for each in tokenized_text:
        ngrams_all[i + 1].extend(ngrams(each, i + 1))
for i in range(4):
    for gram in ngrams_all[i + 1]:
        ngrams_voc[i + 1].add(gram)
total_ngrams = {i + 1: len(ngrams_all[i + 1]) for i in range(4)}
total_voc = {i + 1: len(ngrams_voc[i + 1]) for i in range(4)}
ngrams_prob = {1: [], 2: [], 3: [], 4: []}
for i in range(4):
    for ngram in ngrams_voc[i + 1]:
        count = ngrams_all[i + 1].count(ngram)
        prob = (count + 1) / (total_ngrams[i + 1] + total_voc[i + 1])
        ngrams_prob[i + 1].append((ngram, prob))
### Sort probabilities
for i in range(4):
    ngrams_prob[i + 1].sort(key=lambda x: x[1], reverse=True)
### Prints top 10 unigram, bigram, trigram, fourgram after smoothing
print("Most common n-grams without stopword removal and with add-1 smoothing: \n")
print("Most common unigrams: ", str(ngrams_prob[1][:10]))
print("\nMost common bigrams: ", str(ngrams_prob[2][:10]))
print("\nMost common trigrams: ", str(ngrams_prob[3][:10]))
print("\nMost common fourgrams: ", str(ngrams_prob[4][:10]))
### Next word Prediction
def next_word_prediction(ngram_input, ngrams_prob):
    predictions = []
    for i in range(3):
        count = 0
        for each in ngrams_prob[i + 2]:
            if each[0][:-1] == ngram_input:
                predictions.append(each[0][-1])
                count += 1
                if count == 5:
                    break
        while count < 5:
            predictions.append("NOT FOUND")
            count += 1
    return predictions
str1 = 'after that alice said the'
str2 = 'alice felt so desperate that she was'
token_1 = word_tokenize(str1.lower())
token_2 = word_tokenize(str2.lower())
ngram_1 = {i + 1: list(ngrams(token_1, i + 1))[-1] for i in range(3)}
```

```
ngram_2 = {i + 1: list(ngrams(token_2, i + 1))[-1] for i in range(3)}
print("Next word predictions for the strings using the probability models of bigrams, trigrams, and fourgrams\n")
print("String 1 - after that alice said the-\n")
pred_1 = next_word_prediction(ngram_1[1], ngrams_prob)
print("Bigram model predictions: {}\nTrigram model predictions: {}\nFourgram model predictions: {}\n" .format(pred_1[0], pred_1[1], pred_1[2]))
print("String 2 - alice felt so desperate that she was-\n")
pred_2 = next_word_prediction(ngram_2[1], ngrams_prob)
print("Bigram model predictions: {}\nTrigram model predictions: {}\nFourgram model predictions: {}".format(pred_2[0], pred_2[1], pred_2[2]))
```

Output:

```
(venv) PS D:\Vartak college\sem 7\NLP\EXP\New folder> python .\exp5.py
The number of sentences is 981
The number of tokens is 27361
The average number of tokens per sentence is 28
The number of unique tokens are 3039
Most common n-grams without stopword removal and without add-1 smoothing:
Most common bigrams:  [(('said', 'the'), 209), (('said', 'alice'), 115), (('the', 'queen'), 65), (('the', 'king'), 60), (('a', 'little'), 59)]
Most common trigrams:  [(('the', 'mock', 'turtle'), 51), (('said', 'alice', '.'), 33), (('the', 'march', 'hare'), 30), (('said', 'the', 'king'), 29), (('the', 'white', 'rabbit'), 21)]
Most common fourgrams:  [(('said', 'the', 'mock', 'turtle'), 19), (('she', 'said', 'to', 'herself'), 16), (('said', 'the', 'caterpillar', '.'), 12), (('a', 'minute', 'or', 'two'), 11), (('the', 'march', 'hare', '.'), 10)]
Most common unigrams:  [('said', 462), ('alice', 385), ('little', 128), ('one', 101), ('like', 85), ('know', 85), ('would', 83), ('went', 83), ('could', 77), ('thought', 74)]
Most common bigrams:  [(('said', 'alice'), 122), (('mock', 'turtle'), 54), (('march', 'hare'), 31), (('said', 'king'), 29), (('thought', 'alice'), 26), (('white', 'rabbit'), 22), (('said', 'hatter'), 22), (('said', 'mock'), 20), (('said', 'caterpillar'), 18), (('said', 'gryphon'), 18)]
Most common n-grams without stopword removal and with add-1 smoothing:
Most common unigrams:  [(('the',), 0.05416085541608554), (('.',), 0.03257621040047818), (('and',), 0.028060038520289567), (('to',), 0.023975559540413097), (('a',), 0.020854087799694495), (('she',), 0.01786544464368732), (('it',), 0.017500166035730888), (('of',), 0.016902437404529454), (('said',), 0.01537490868034801), (('i',), 0.013316065617320847)]
Most common bigrams:  [(('said', 'the'), 0.00514718498002402), (('of', 'the'), 0.0032108630113483172), (('said', 'alice'), 0.002843206941346602), (('in', 'a'), 0.0024020196573445425), (('and83172), (('said', 'alice'), 0.002843206941346602), (('in', 'a'), 0.0024020196573445425), (('and', 'the'), 0.001985342778009265), (('in', 'the'), 0.0019363219686757028), (('it', 'was'), 0.0018382803500085786), (('to', 'the'), 0.0017157283266746733), (('the', 'queen'), 0.0016176867080075492), (('as', 'she'), 0.0015196450893340425)]
Most common trigrams:  [(('the', 'mock', 'turtle'), 0.0011025358324145535), (('said', 'alice', ', 'the'), 0.001985342778009265), (('in', 'the'), 0.0019363219686757028), (('it', 'was'), 0.0018382803500085786), (('to', 'the'), 0.0017157283266746733), (('the', 'queen'), 0.0016176867080075492), (('as', 'she'), 0.0015196450893340425)]
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Most common trigrams: [(('the', 'mock', 'turtle'), 0.0011025358324145535), (('said', 'alice',
5492), (('as', 'she'), 0.0015196450893404425)]
Most common trigrams: [(('the', 'mock', 'turtle'), 0.0011025358324145535), (('said', 'alice', '.'),
0.0007208888135018235), (('the', 'march', 'hare'), 0.0006572809770163684), (('said', 'the',
'king'), 0.0006360783648545501), (('said', 'the', 'hatter'), 0.0004664574675600034), (('the',
'white', 'rabbit'), 0.0004664574675600034), (('said', 'to', 'herself'), 0.00042405224323636667
Most common trigrams: [(('the', 'mock', 'turtle'), 0.0011025358324145535), (('said', 'alice', '.'),
0.0007208888135018235), (('the', 'march', 'hare'), 0.0006572809770163684), (('said', 'the',
'king'), 0.0006360783648545501), (('said', 'the', 'hatter'), 0.0004664574675600034), (('the',
'white', 'rabbit'), 0.0004664574675600034), (('said', 'to', 'herself'), 0.00042405224323636667),
(('said', 'the', 'mock'), 0.00042405224323636667), (('said', 'the', 'caterpillar'),
0.0004028496310745484), (('said', 'the', 'gryphon'), 0.00038164701891273004)]
'.'), 0.0007208888135018235), (('the', 'march', 'hare'), 0.0006572809770163684), (('said', 'the',
'king'), 0.0006360783648545501), (('said', 'the', 'hatter'), 0.0004664574675600034), (('the',
'white', 'rabbit'), 0.0004664574675600034), (('said', 'to', 'herself'), 0.00042405224323636667),
(('said', 'the', 'mock'), 0.00042405224323636667), (('said', 'the', 'caterpillar'),
0.0004028496310745484), (('said', 'the', 'gryphon'), 0.00038164701891273004)]
), (('said', 'the', 'mock'), 0.00042405224323636667), (('said', 'the', 'caterpillar'),
0.0004028496310745484), (('said', 'the', 'gryphon'), 0.00038164701891273004)]
496310745484), (('said', 'the', 'gryphon'), 0.00038164701891273004)]
Most common fourgrams: [(('said', 'the', 'mock', 'turtle'), 0.00041860270417346895), (('she',
Most common fourgrams: [(('said', 'the', 'mock', 'turtle'), 0.00041860270417346895), (('she',
'said', 'to', 'herself'), 0.0003558122985474486), (('said', 'the', 'caterpillar', '.'),
0.0002720917577127548), (('a', 'minute', 'or', 'two'), 0.0002511616225040814), (('said', 'the',
'king', '.'), 0.00023023148729540792), (('the', 'march', 'hare', '.'), 0.00023023148729540792),
(('said', 'the', 'hatter', '.'), 0.00020930135208673448), (('will', 'you', 'wont', 'you'),
0.00018837121687806103), (('said', 'the', 'march', 'hare'), 0.00018837121687806103), (('the',
'mock', 'turtle', '.'), 0.00018837121687806103)]
Next word predictions for the strings using the probability models of bigrams, trigrams, and fourgrams
String 1 - after that alice said the-
Bigram model predictions: queen
Trigram model predictions: king
Fourgram model predictions: mock
String 2 - alice felt so desperate that she was-
Bigram model predictions: a
Trigram model predictions: the
Fourgram model predictions: not

Conclusion:

The N-gram language model was implemented for text analysis, generating unigrams, igrams, trigrams, and fourgrams from a dataset. Key statistics included 981 sentences, 27,361 tokens, and 3,039 unique tokens. Most common n-grams were identified, with bigrams like ('said', 'the') and trigrams like ('the', 'mock', 'turtle') being the most frequent. Add-1 smoothing was applied to enhance the probability distribution. Next-word predictions were made for two input strings, yielding various bigram and trigram predictions. The model effectively captures word patterns but showed limitations in fourgram predictions, indicating a need for more data or refinement for improved accuracy.