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Experiment No.5
Implement Bi-Gram model for the given Text input
Date of Performance:
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Aim: Implement Bi-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

Output:

Necessary Imports

In [ ]:
```
import nltk, re, pprint, string
nltk.download('punkt')
nltk.download('stopwords')
from nltk import word_tokenize, sent_tokenize
string.punctuation = string.punctuation +'“'+'”'+'-'+'’'+'‘'+'—'
string.punctuation = string.punctuation.replace('.', '')
file = open('/content/drive/MyDrive/nlp lab/dataset.txt', encoding = 'utf8').read()
```

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

In [ ]:
```
from google.colab import drive
drive.mount('/content/drive')
```

```
Mounted at /content/drive
```

Preprocess of the Data

In [ ]:
```
file_nl_removed = ""
for line in file:
  line_nl_removed = line.replace("\n", " ")
  file_nl_removed += line_nl_removed
file_p = "".join([char for char in file_nl_removed if char not in string.punctuation])
```

Statistics of the Data

In [ ]:
```
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))
```

```
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
```

Building the N-Gram Model

In [ ]:
```
from nltk.util import ngrams
from nltk.corpus import stopwords
stop_words = set(stopwords.words('english'))
```

In [ ]:
```
unigram=[]
bigram=[]
trigram=[]
fourgram=[]
tokenized_text = []
```

In [ ]:
```
for sentence in sents:
    sentence = sentence.lower()
    sequence = word_tokenize(sentence)
    for word in sequence:
        if (word =='.'):
            sequence.remove(word)
        else:
            unigram.append(word)
    tokenized_text.append(sequence)
    bigram.extend(list(ngrams(sequence, 2)))
    trigram.extend(list(ngrams(sequence, 3)))
    fourgram.extend(list(ngrams(sequence, 4)))
```

```
                count = count or 0
            else:
                count = count or 1
        if (count==1):
            y.append(pair)
    return(y)


bigram = removal(bigram)
trigram = removal(trigram)
fourgram = removal(fourgram)
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))
```

```
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', 'kin
g'), 60), (('a', 'little'), 59)]

Most common trigrams:  [(('the', 'mock', 'turtle'), 51), (('the', 'march', 'hare'), 30), (('said', 'the', 'kin
g'), 29), (('the', 'white', 'rabbit'), 21), (('said', 'the', 'hatter'), 21)]

Most common fourgrams:  [(('said', 'the', 'mock', 'turtle'), 19), (('she', 'said', 'to', 'herself'), 16), (('a',
'minute', 'or', 'two'), 11), (('said', 'the', 'march', 'hare'), 8), (('will', 'you', 'wont', 'you'), 8)]
```

Script for downloading the stopwords using NLTK

In [ ]:

```
from nltk.corpus import stopwords
stop_words = set(stopwords.words('english'))
```

Print 10 Unigrams and Bigrams after removing stopwords

In [ ]:

```
print("Most common n-grams with stopword removal and without add-1 smoothing: \n")
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 = []
bigram_sw_removed.extend(list(ngrams(unigram_sw_removed, 2)))
fdist = nltk.FreqDist(bigram_sw_removed)
print("\nMost common bigrams: ", fdist.most_common(10))
```

```
Most common n-grams with stopword removal and without add-1 smoothing:

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', 'ki
ng'), 29), (('thought', 'alice'), 26), (('white', 'rabbit'), 22), (('said', 'hatter'), 22), (('said', 'mock'), 2
0), (('said', 'caterpillar'), 18), (('said', 'gryphon'), 18)]
```

Add-1 smoothing

In [ ]:

```
ngrams_all = {1:[], 2:[], 3:[], 4:[]}
for i in range(4):
    for each in tokenized_text:
        for j in ngrams(each, i+1):
            ngrams_all[i+1].append(j);
ngrams_voc = {1:set([]), 2:set([]), 3:set([]), 4:set([])}
for i in range(4):
    for gram in ngrams_all[i+1]:
        if gram not in ngrams_voc[i+1]:
            ngrams_voc[i+1].add(gram)
total_ngrams = {1:-1, 2:-1, 3:-1, 4:-1}
total_voc = {1:-1, 2:-1, 3:-1, 4:-1}
for i in range(4):
    total_ngrams[i+1] = len(ngrams_all[i+1])
    total_voc[i+1] = len(ngrams_voc[i+1])

ngrams_prob = {1:[], 2:[], 3:[], 4:[]}
for i in range(4):
    for ngram in ngrams_voc[i+1]:
        tlist = [ngram]
        tlist.append(ngrams_all[i+1].count(ngram))
        ngrams_prob[i+1].append(tlist)

for i in range(4):
    for ngram in ngrams_prob[i+1]:
        ngram[-1] = (ngram[-1]+1)/(total_ngrams[i+1]+total_voc[i+1])
```

Prints top 10 unigram, bigram, trigram, fourgram after smoothing

In [ ]:
```
print("Most common n-grams without stopword removal and with add-1 smoothing: \n")
for i in range(4):
    ngrams_prob[i+1] = sorted(ngrams_prob[i+1], key = lambda x:x[1], reverse = True)

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]))
```

```
Most common n-grams without stopword removal and with add-1 smoothing:

Most common unigrams:  [[('the',), 0.05598462224968249], [('and',), 0.02900490852298081], [('to',), 0.02478289225277177],
[('a',), 0.02155631071293722], [('she',), 0.018467030515223287], [('it',), 0.018089451824391582], [('of',), 0.0174715957848487
97], [('said',), 0.015892630350461675], [('i',), 0.013764459547592077], [('alice',), 0.013249579514639755]]

Most common bigrams:  [[('said', 'the'), 0.005339571308703501 6], [('of', 'the'), 0.0033308754354293268], [('said', 'alice'),
0.0029494774848076483], [('in', 'a'), 0.002491799944061634], [('and', 'the'), 0.002059548933357065], [('in', 'the'), 0.0020086
958732741743], [('it', 'was'), 0.0019069897531083933], [('to', 'the'), 0.0017798571029011671], [('the', 'queen'), 0.0016781509
827353861], [('as', 'she'), 0.0015764448625696051]]

Most common trigrams:  [[('the', 'mock', 'turtle'), 0.001143837575064341], [('the', 'march', 'hare'), 0.0006819031697498955],
[('said', 'the', 'king'), 0.0006599062933063505], [('the', 'white', 'rabbit'), 0.00048393128175799036], [('said', 'the', 'hatt
er'), 0.00048393128175799036], [('said', 'the', 'mock'), 0.0004399375288709003], [('said', 'to', 'herself'), 0.000439937528870
9003], [('said', 'the', 'caterpillar'), 0.0004179406524273553], [('said', 'the', 'gryphon'), 0.0003959437759838103], [('she',
'went', 'on'), 0.0003959437759838103]]

Most common fourgrams:  [[('said', 'the', 'mock', 'turtle'), 0.00043521782652217433], [('she', 'said', 'to', 'herself'), 0.000
3699351525438482], [('a', 'minute', 'or', 'two'), 0.0002611306959133046], [('said', 'the', 'march', 'hare'), 0.000195848021934
97845], [('will', 'you', 'wont', 'you'), 0.00019584802193497845], [('said', 'alice', 'in', 'a'), 0.00017408713060886974], [('i
n', 'a', 'great', 'hurry'), 0.0001523262392827610 2], [('you', 'wont', 'you', 'will'), 0.0001523262392827610 2], [('as', 'well',
```

Next word Prediction

In [ ]:
```
str1 = 'after that alice said the'
str2 = 'alice felt so desperate that she was'
```

In [ ]:
```
token_1 = word_tokenize(str1)
token_2 = word_tokenize(str2)
ngram_1 = {1:[], 2:[], 3:[]}   #to store the n-grams formed
ngram_2 = {1:[], 2:[], 3:[]}
for i in range(3):
    ngram_1[i+1] = list(ngrams(token_1, i+1))[-1]
    ngram_2[i+1] = list(ngrams(token_2, i+1))[-1]
print("String 1: ", ngram_1,"\nString 2: ",ngram_2)
```

```
String 1:  {1: ('the',), 2: ('said', 'the'), 3: ('alice', 'said', 'the')}
String 2:  {1: ('was',), 2: ('she', 'was'), 3: ('that', 'she', 'was')}
```

In [ ]:
```
for i in range(4):
    ngrams_prob[i+1] = sorted(ngrams_prob[i+1], key = lambda x:x[1], reverse = True)

pred_1 = {1:[], 2:[], 3:[]}
for i in range(3):
    count = 0
    for each in ngrams_prob[i+2]:
        if each[0][:-1] == ngram_1[i+1]:
#to find predictions based on highest probability of n-grams

            count +=1
            pred_1[i+1].append(each[0][-1])
            if count ==5:
```

```
                count +=1
                pred_1[i+1].append(each[0][-1])
                if count ==5:
                    break
        if count<5:
            while(count!=5):
                pred_1[i+1].append("NOT FOUND")
#if no word prediction is found, replace with NOT FOUND
                count +=1
for i in range(4):
    ngrams_prob[i+1] = sorted(ngrams_prob[i+1], key = lambda x:x[1], reverse = True)

pred_2 = {1:[], 2:[], 3:[]}
for i in range(3):
    count = 0
    for each in ngrams_prob[i+2]:
        if each[0][:-1] == ngram_2[i+1]:
            count +=1
            pred_2[i+1].append(each[0][-1])
            if count ==5:
                break
    if count<5:
        while(count!=5):
            pred_2[i+1].append("\0")
            count +=1
```

In [ ]:

```
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")
print("Bigram model predictions: {}\nTrigram model predictions: {}\nFourgram model predictions: {}\n" .format(pred_1[1], pre
print("String 2 - alice felt so desperate that she was-\n")
print("Bigram model predictions: {}\nTrigram model predictions: {}\nFourgram model predictions: {}" .format(pred_2[1], pred_
```

```
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', 'king', 'gryphon', 'mock', 'hatter']
Trigram model predictions: ['king', 'hatter', 'mock', 'caterpillar', 'gryphon']
Fourgram model predictions: ['NOT FOUND', 'NOT FOUND', 'NOT FOUND', 'NOT FOUND', 'NOT FOUND']

String 2 - alice felt so desperate that she was-

Bigram model predictions: ['a', 'the', 'not', 'going', 'that']
Trigram model predictions: ['now', 'quite', 'a', 'walking', 'beginning']
Fourgram model predictions: ['now', 'quite', 'dozing', 'losing', 'ready']
```

Conclusion:

N-gram language models are statistical models that predict the next word in a sequence based on the previous N-1 words. They are often used in NLP tasks such as speech recognition, machine translation, and text generation. The results of N-gram language models depend on the size and quality of the training corpus, the order of the N-gram model, and the smoothing algorithm used. In general, N-gram language models are effective in a variety of NLP tasks, but they can be computationally expensive to train and use, and they may not perform well on data that is different from the training corpus.