Query Likelihood Model

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INTRODUCTION

Information Retrieval is the activity of obtaining material that can usually be documented on an unstructured nature i.e., usually text which satisfies an information need from within large collections which is stored on computers. For example, Information Retrieval can be when a user enters a query into the system.

Not only librarians, professional searchers, etc. engage themselves in the activity of information retrieval but nowadays hundreds of millions of people engage in IR every day when they use web search engines. Information Retrieval is believed to be the dominant form of Information access.

The IR system assists the users in finding the information they require but it does not explicitly return the answers to the question. It notifies regarding the existence and location of documents that might consist of the required information. Information retrieval also extends support to users in browsing or filtering document collection or processing a set of retrieved documents. The system searches over billions of documents stored on millions of computers. A spam filter, manual or automatic means are provided by email program for classifying the mails so that it can be placed directly into folders.

Information Retrieval (IR), (more precisely, text information retrieval) is a branch of computer science that deals with the processing of collections of documents containing ‘free text’, such as scientific papers, or even the contents of electronic textbooks. The objective of such processing is to facilitate rapid and accurate search of the text based on keywords of interest.

Types of IR Models

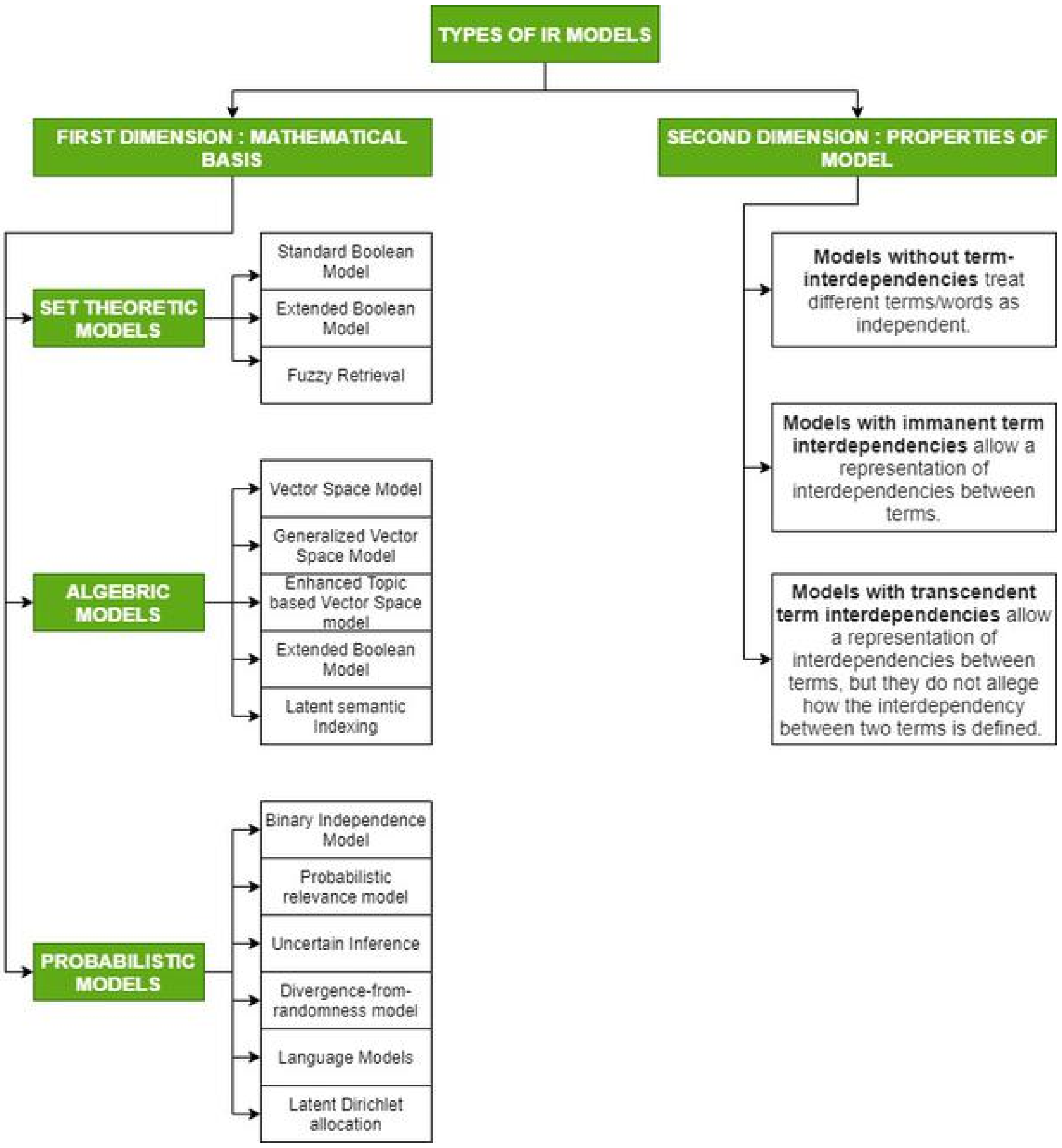

TYPES OF IR MODELS
FIRST DIMENSION : MATHEMATICAL BASIS
SECOND DIMENSION : PROPERTIES OF MODEL
SET THEORETIC MODELS
Standard Boolean Model
Extended Boolean Model
Fuzzy Retrieval
ALGEBRIC MODELS
Vector Space Model
Generalized Vector Space Model
Enhanced Topic based Vector Space model
Extended Boolean Model
Latent semantic Indexing
PROBABILISTIC MODELS
Binary Independence Model
Probabilistic relevance model
Uncertain Inference
Divergence-from-randomness model
Language Models
Latent Dirichlet allocation
Models without term-interdependencies treat different terms/words as independent.
Models with immanent term interdependencies allow a representation of interdependencies between terms.
Models with transcendent term interdependencies allow a representation of interdependencies between terms, but they do not allege how the interdependency between two terms is defined.

Figure 1 Types of IR models

Components of Information Retrieval/ IR Model

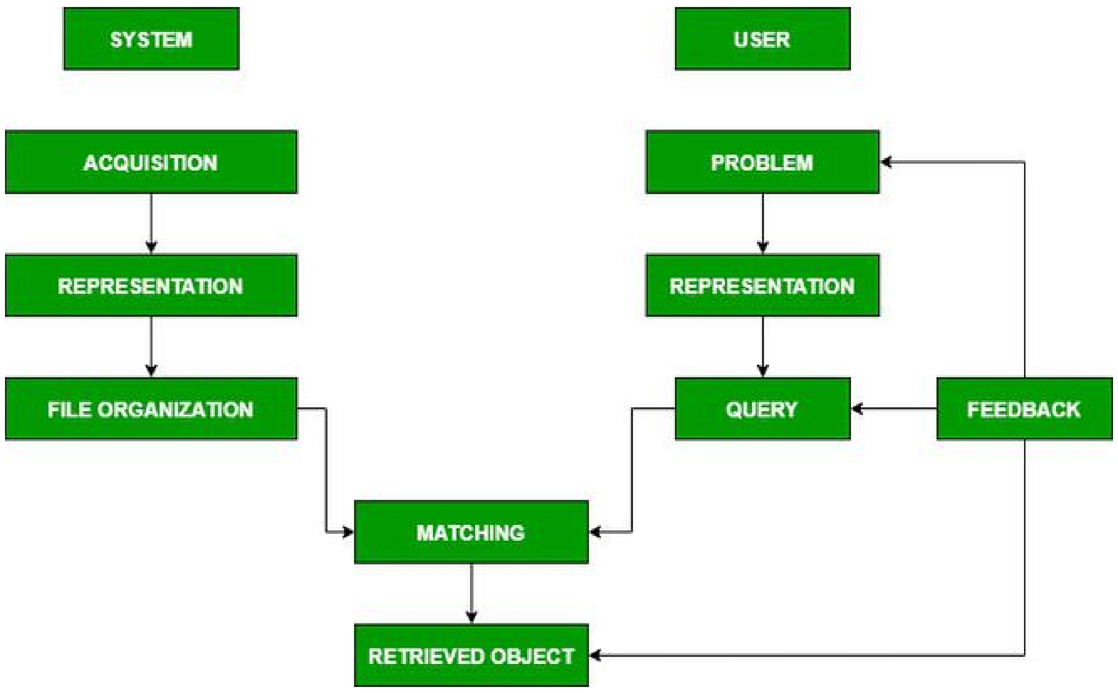


Figure 2 Components of Information Retrieval/ IR Model

In this project we will apply one of the language models (Query likelihood model).

Query Likelihood Model

Over the past three decades, probabilistic models of document retrieval have been studied extensively. In general, these approaches can be characterized as methods of estimating the probability of relevance of documents to user queries.

The goal of a language model is to assign a probability to a sequence of words by means of a probability distribution”

The query likelihood model is a language model used in information retrieval. A language model is constructed for each document in the collection. It is then possible to rank each document by the probability of specific documents given a query. This is interpreted as being the likelihood of a document being relevant given a query.

The main purpose of this to put the core Information Retrieval concepts into practice by building and using our very own retrieval systems.

The Aim of this project

The aim of this project is to build retrieval systems using the query likelihood model, which will show the percentage of the probability of the query being in each file.

IMPLEMENTATION

Overview of the techniques used in the project

- Query Likelihood: Foundation for this model is taken using Baye’s rule which states as below.

  $$p(D|Q) \overset{rank}{=} P(Q|D)P(D)$$

- Removes all punctuations from a string.

- Stopping word: It’s the process of removing common words from the stream of tokens that become index terms. Stop words are taken into a list and while parsing the document for indexing, if the word is present in the stop word list, that word is not added to the inverted index.

- Tokenization: is essentially splitting a phrase, sentence, paragraph, or an entire text document into smaller units, such as individual words or terms. Each of these smaller units are called tokens.

- Stemming: The task of stemming component is to group words that are derived from a common stem.

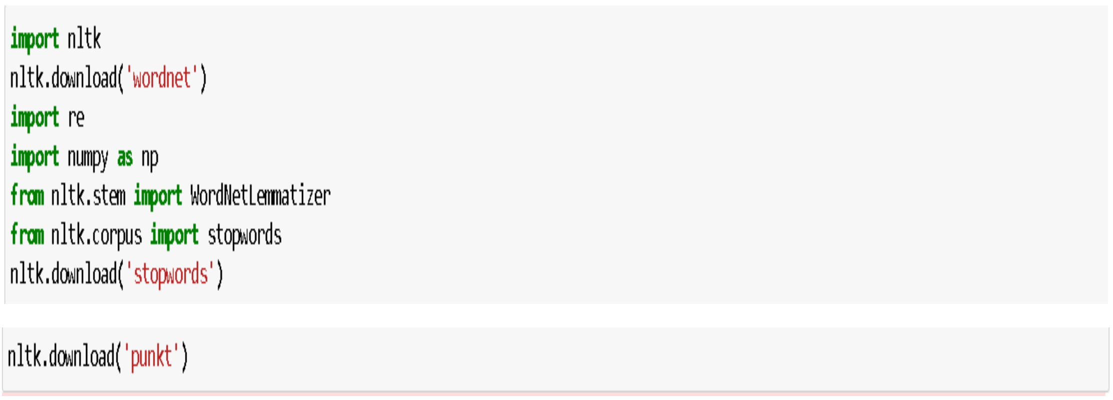
- Lemmatization: is the process of grouping together the inflected forms of a word so they can be analyzed as a single item, identified by the word's lemma, or dictionary form.

<u>Note: Lemmatization and stemming work in a similar way with a slight difference, so using one of them is enough, but in this project, I preferred to use them together for better results.</u>

Code

In this project, Query Likelihood Model has been implemented that contains all text processing.

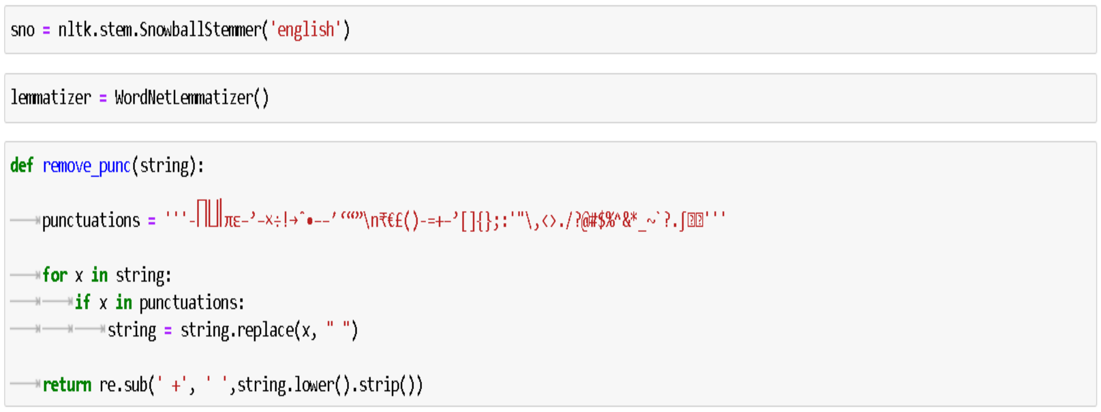
First, we need to initialize and import all the libraries we need in the code.



```
import nltk
nltk.download('wordnet')
import re
import numpy as np
from nltk.stem import WordNetLemmatizer
from nltk.corpus import stopwords
nltk.download('stopwords')
```

```
nltk.download('punkt')
```

Then we start by defining some of the functions we want to use on the documents.

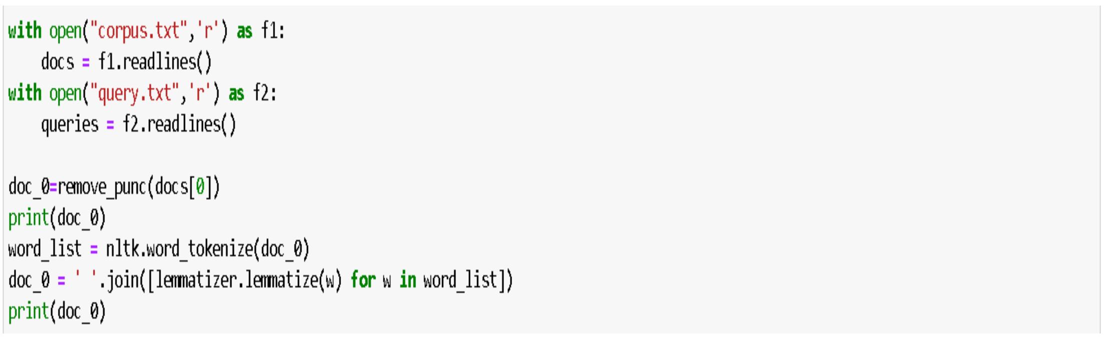


```
sno = nltk.stem.SnowballStemmer('english')
```

```
lemmatizer = WordNetLemmatizer()
```

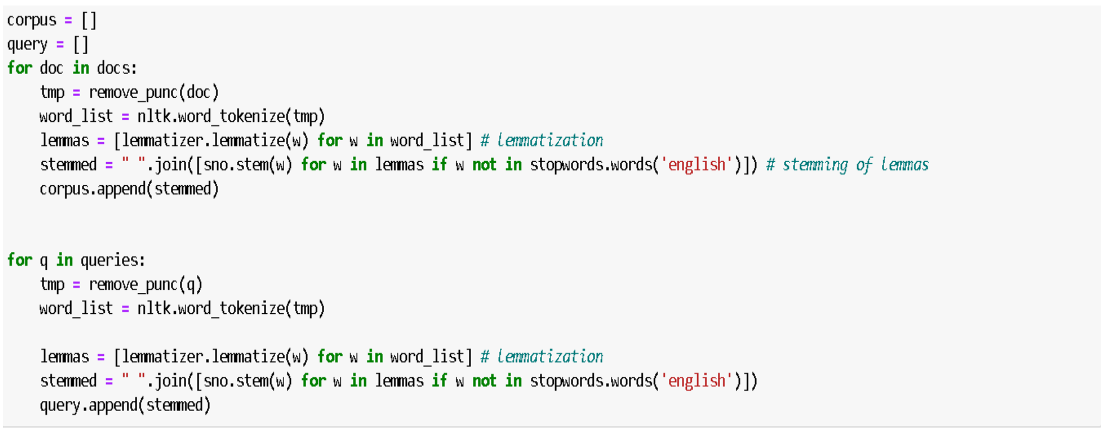
```
def remove_punc(string):

    punctuations = '''-∏∐|πε–’–×÷!→ˆ•––‘“”\n₹€£()-=+–’[]{};:'"\,<>./?@#$%^&*_~`?.∫⍰⍰'''

    for x in string:
        if x in punctuations:
            string = string.replace(x, " ")

    return re.sub(' +', ' ',string.lower().strip())
```

At this point we will start reading the files, the corpus containing all the text documents, and the query containing the queries we will apply on documents.

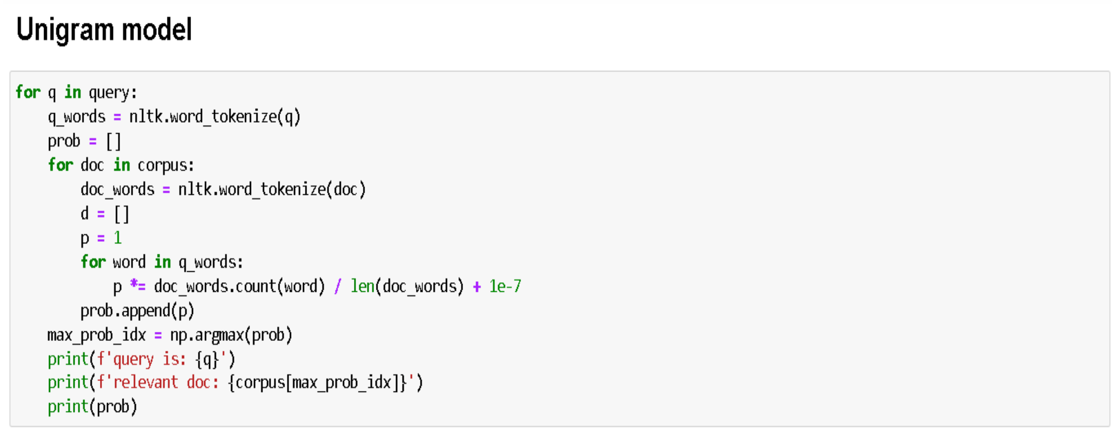


```
with open("corpus.txt",'r') as f1:
    docs = f1.readlines()
with open("query.txt",'r') as f2:
    queries = f2.readlines()

doc_0=remove_punc(docs[0])
print(doc_0)
word_list = nltk.word_tokenize(doc_0)
doc_0 = ' '.join([lemmatizer.lemmatize(w) for w in word_list])
print(doc_0)
```

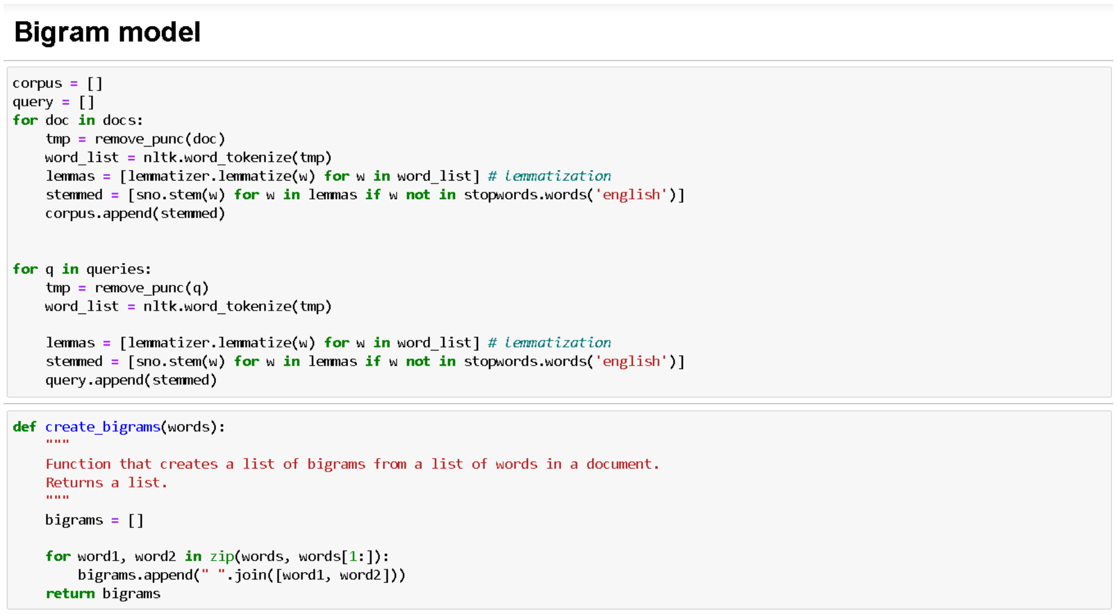
After we defined the text processing above, here we begin to apply them to both the document and the query.


```python
corpus = []
query = []
for doc in docs:
    tmp = remove_punc(doc)
    word_list = nltk.word_tokenize(tmp)
    lemmas = [lemmatizer.lemmatize(w) for w in word_list] # lemmatization
    stemmed = " ".join([sno.stem(w) for w in lemmas if w not in stopwords.words('english')]) # stemming of lemmas
    corpus.append(stemmed)


for q in queries:
    tmp = remove_punc(q)
    word_list = nltk.word_tokenize(tmp)

    lemmas = [lemmatizer.lemmatize(w) for w in word_list] # lemmatization
    stemmed = " ".join([sno.stem(w) for w in lemmas if w not in stopwords.words('english')])
    query.append(stemmed)
```

Now we start executing Query Likelihood Model.


Unigram model

```python
for q in query:
    q_words = nltk.word_tokenize(q)
    prob = []
    for doc in corpus:
        doc_words = nltk.word_tokenize(doc)
        d = []
        p = 1
        for word in q_words:
            p *= doc_words.count(word) / len(doc_words) + 1e-7
        prob.append(p)
    max_prob_idx = np.argmax(prob)
    print(f'query is: {q}')
    print(f'relevant doc: {corpus[max_prob_idx]}')
    print(prob)
```


Bigram model

```python
corpus = []
query = []
for doc in docs:
    tmp = remove_punc(doc)
    word_list = nltk.word_tokenize(tmp)
    lemmas = [lemmatizer.lemmatize(w) for w in word_list] # lemmatization
    stemmed = [sno.stem(w) for w in lemmas if w not in stopwords.words('english')]
    corpus.append(stemmed)


for q in queries:
    tmp = remove_punc(q)
    word_list = nltk.word_tokenize(tmp)

    lemmas = [lemmatizer.lemmatize(w) for w in word_list] # lemmatization
    stemmed = [sno.stem(w) for w in lemmas if w not in stopwords.words('english')]
    query.append(stemmed)
```

```python
def create_bigrams(words):
    """
    Function that creates a list of bigrams from a list of words in a document.
    Returns a list.
    """
    bigrams = []

    for word1, word2 in zip(words, words[1:]):
        bigrams.append(" ".join([word1, word2]))
    return bigrams
```

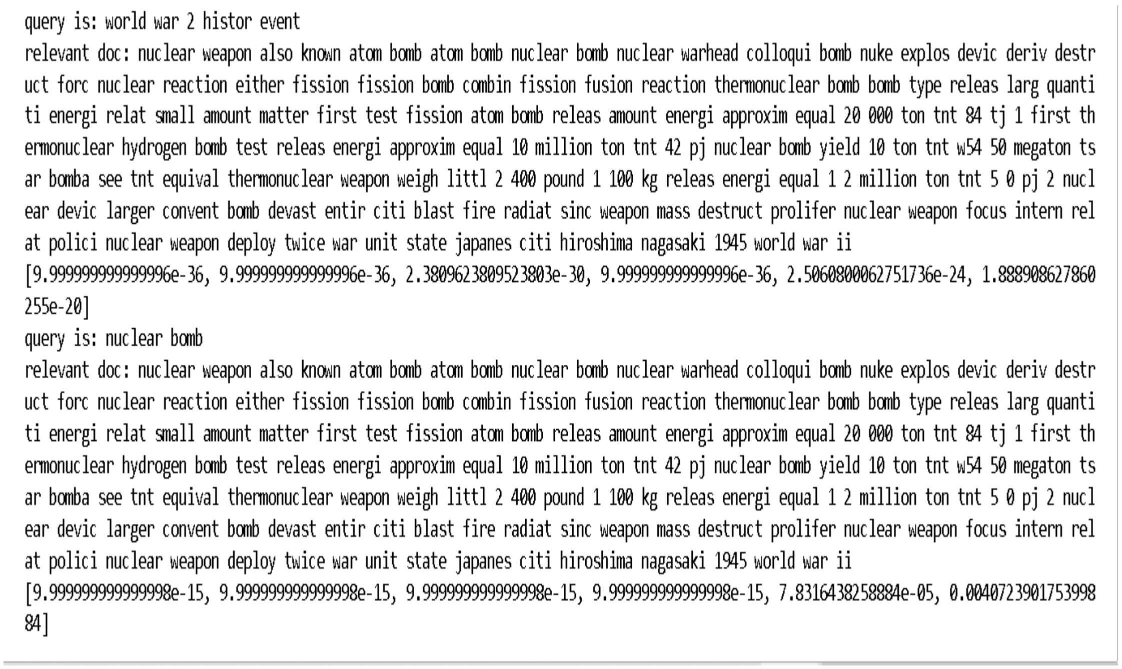
```python
for q in query:
    query_bigrams = create_bigrams(q)

    prob = []
    for doc in corpus:
        doc_bigrams = create_bigrams(doc)
        p = 1
        for bigram in query_bigrams:
            p *= doc_bigrams.count(bigram) / len(doc_bigrams) + 1e-7

        prob.append(p)
    max_prob_idx = np.argmax(prob)

    q = " ".join(q)
    d = " ".join(corpus[max_prob_idx])
    print(f'query is: {q}')
    print(f'relevant doc: {d}')
    print(prob)
    print()
```

Result and output

The outputs and results are divided into two parts, the first for Unigram, and the other for Bigram.

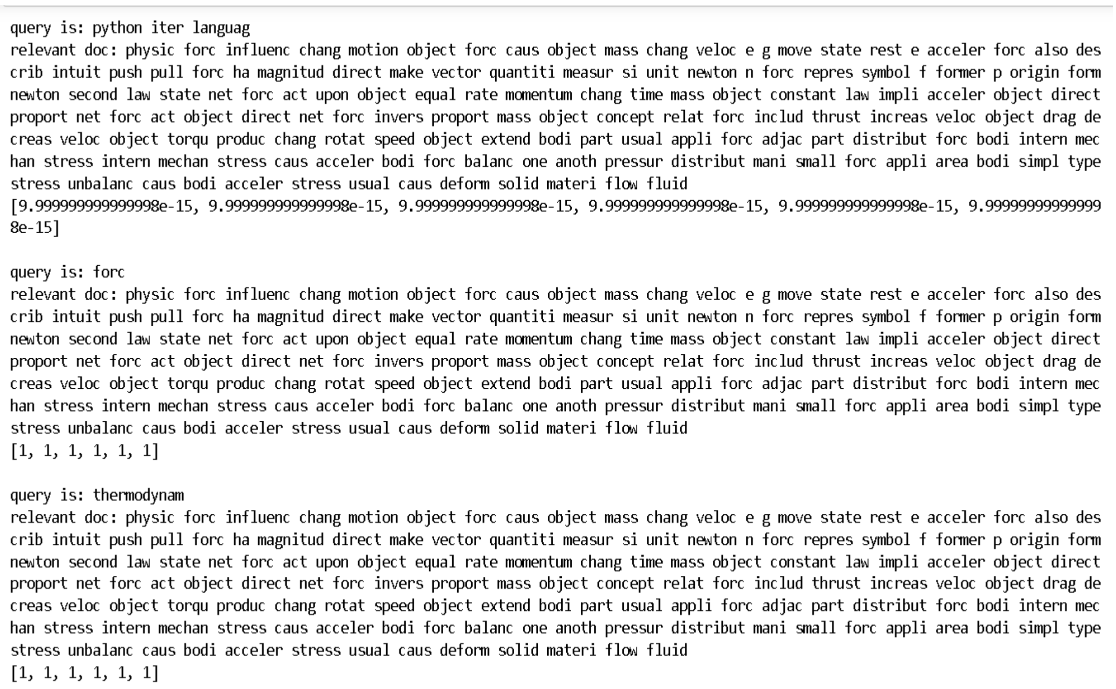
The outputs for Unigram

```
query is: python iter languag
relevant doc: python interpret high level general purpos program languag design philosophi emphas code readabl use signific indent l
anguag construct well object orient approach aim help programm write clear logic code small larg scale project python dynam type gar
bag collect support multipl program paradigm includ structur particular procedur object orient function program often describ batter
i includ languag due comprehens standard librari guido van rossum began work python late 1980s successor abc program languag first r
eleas 1991 python 0 9 0 python 2 0 wa releas 2000 introduc new featur list comprehens cycl detect garbag collect system addit refer
count python 3 0 wa releas 2008 wa major revis languag complet backward compat python 2 wa discontinu version 2 7 18 2020 python con
sist rank one popular program languag
[9.999999999999997e-22, 7.407507407407407e-17, 3.0234427059812774e-10, 8.849657522123892e-17, 9.999999999999997e-22, 9.9999999999999
97e-22]
query is: forc
relevant doc: physic forc influenc chang motion object forc caus object mass chang veloc e g move state rest e acceler forc also des
crib intuit push pull forc ha magnitud direct make vector quantiti measur si unit newton n forc repres symbol f former p origin form
newton second law state net forc act upon object equal rate momentum chang time mass object constant law impli acceler object direct
proport net forc act object direct net forc invers proport mass object concept relat forc includ thrust increas veloc object drag de
creas veloc object torqu produc chang rotat speed object extend bodi part usual appli forc adjac part distribut forc bodi intern mec
han stress intern mechan stress caus acceler bodi forc balanc one anoth pressur distribut mani small forc appli area bodi simpl type
stress unbalanc caus bodi acceler stress usual caus deform solid materi flow fluid
[0.09027787777777778, 1e-07, 1e-07, 1e-07, 1e-07, 0.006802821088435374]
query is: thermodynam
relevant doc: thermodynam heat energi transfer thermodynam system mechan thermodynam work transfer matter various mechan energi tran
sfer defin heat state next section articl like thermodynam work heat transfer process involv one system properti one system thermody
nam energi transfer heat contribut chang system cardin energi variabl state exampl intern energi exampl enthalpi distinguish ordinar
i languag concept heat properti isol system quantiti energi transfer heat process amount transfer energi exclud thermodynam work wa
done energi contain matter transfer precis definit heat necessari occur path doe includ transfer matter though immedi definit specia
l kind process quantiti energi transfer heat measur effect state interact bodi exampl respect special circumst heat transfer measur
amount ice melt chang temperatur bodi surround system method call calorimetri convent symbol use repres amount heat transfer thermod
ynam process q amount energi transfer si unit heat joul j
[1e-07, 0.05185185185185185, 1e-07, 1e-07, 1e-07, 1e-07]
```



```
query is: world war 2 histor event
relevant doc: nuclear weapon also known atom bomb atom bomb nuclear bomb nuclear warhead colloqui bomb nuke explos devic deriv destr
uct forc nuclear reaction either fission fission bomb combin fission fusion reaction thermonuclear bomb bomb type releas larg quanti
ti energi relat small amount matter first test fission atom bomb releas amount energi approxim equal 20 000 ton tnt 84 tj 1 first th
ermonuclear hydrogen bomb test releas energi approxim equal 10 million ton tnt 42 pj nuclear bomb yield 10 ton tnt w54 50 megaton ts
ar bomba see tnt equival thermonuclear weapon weigh littl 2 400 pound 1 100 kg releas energi equal 1 2 million ton tnt 5 0 pj 2 nucl
ear devic larger convent bomb devast entir citi blast fire radiat sinc weapon mass destruct prolifer nuclear weapon focus intern rel
at polici nuclear weapon deploy twice war unit state japanes citi hiroshima nagasaki 1945 world war ii
[9.999999999999996e-36, 9.999999999999996e-36, 2.3809623809523803e-30, 9.999999999999996e-36, 2.5060800062751736e-24, 1.888908627860
255e-20]
query is: nuclear bomb
relevant doc: nuclear weapon also known atom bomb atom bomb nuclear bomb nuclear warhead colloqui bomb nuke explos devic deriv destr
uct forc nuclear reaction either fission fission bomb combin fission fusion reaction thermonuclear bomb bomb type releas larg quanti
ti energi relat small amount matter first test fission atom bomb releas amount energi approxim equal 20 000 ton tnt 84 tj 1 first th
ermonuclear hydrogen bomb test releas energi approxim equal 10 million ton tnt 42 pj nuclear bomb yield 10 ton tnt w54 50 megaton ts
ar bomba see tnt equival thermonuclear weapon weigh littl 2 400 pound 1 100 kg releas energi equal 1 2 million ton tnt 5 0 pj 2 nucl
ear devic larger convent bomb devast entir citi blast fire radiat sinc weapon mass destruct prolifer nuclear weapon focus intern rel
at polici nuclear weapon deploy twice war unit state japanes citi hiroshima nagasaki 1945 world war ii
[9.999999999999998e-15, 9.999999999999998e-15, 9.999999999999998e-15, 9.999999999999998e-15, 7.8316438258884e-05, 0.0040723901753998
84]
```

The outputs for Bigram



```
query is: python iter languag
relevant doc: physic forc influenc chang motion object forc caus object mass chang veloc e g move state rest e acceler forc also des
crib intuit push pull forc ha magnitud direct make vector quantiti measur si unit newton n forc repres symbol f former p origin form
newton second law state net forc act upon object equal rate momentum chang time mass object constant law impli acceler object direct
proport net forc act object direct net forc invers proport mass object concept relat forc includ thrust increas veloc object drag de
creas veloc object torqu produc chang rotat speed object extend bodi part usual appli forc adjac part distribut forc bodi intern mec
han stress intern mechan stress caus acceler bodi forc balanc one anoth pressur distribut mani small forc appli area bodi simpl type
stress unbalanc caus bodi acceler stress usual caus deform solid materi flow fluid
[9.999999999999998e-15, 9.999999999999998e-15, 9.999999999999998e-15, 9.999999999999998e-15, 9.999999999999998e-15, 9.99999999999999
8e-15]

query is: forc
relevant doc: physic forc influenc chang motion object forc caus object mass chang veloc e g move state rest e acceler forc also des
crib intuit push pull forc ha magnitud direct make vector quantiti measur si unit newton n forc repres symbol f former p origin form
newton second law state net forc act upon object equal rate momentum chang time mass object constant law impli acceler object direct
proport net forc act object direct net forc invers proport mass object concept relat forc includ thrust increas veloc object drag de
creas veloc object torqu produc chang rotat speed object extend bodi part usual appli forc adjac part distribut forc bodi intern mec
han stress intern mechan stress caus acceler bodi forc balanc one anoth pressur distribut mani small forc appli area bodi simpl type
stress unbalanc caus bodi acceler stress usual caus deform solid materi flow fluid
[1, 1, 1, 1, 1, 1]

query is: thermodynam
relevant doc: physic forc influenc chang motion object forc caus object mass chang veloc e g move state rest e acceler forc also des
crib intuit push pull forc ha magnitud direct make vector quantiti measur si unit newton n forc repres symbol f former p origin form
newton second law state net forc act upon object equal rate momentum chang time mass object constant law impli acceler object direct
proport net forc act object direct net forc invers proport mass object concept relat forc includ thrust increas veloc object drag de
creas veloc object torqu produc chang rotat speed object extend bodi part usual appli forc adjac part distribut forc bodi intern mec
han stress intern mechan stress caus acceler bodi forc balanc one anoth pressur distribut mani small forc appli area bodi simpl type
stress unbalanc caus bodi acceler stress usual caus deform solid materi flow fluid
[1, 1, 1, 1, 1, 1]
```

```
query is: world war 2 histor event
relevant doc: world war ii second world war often abbrevi wwii ww2 wa global war last 1939 1945 involv vast major world countriesâ i
nclud great powersâ form two oppos militari allianc alli axi power total war direct involv 100 million personnel 30 countri major pa
rticip threw entir econom industri scientif capabl behind war effort blur distinct civilian militari resourc aircraft play major rol
e conflict enabl strateg bomb popul centr two us nuclear weapon war day world war ii wa far deadliest conflict human histori result
70 85 million fatal major civilian ten million peopl die due genocid includ holocaust starvat massacr diseas wake axi defeat germani
japan occupi war crime tribun conduct german japanes leader
[9.999999999999996e-29, 9.999999999999996e-29, 9.999999999999996e-29, 9.999999999999996e-29, 2.678581428571428e-23, 6.84941506849314
9e-24]

query is: nuclear bomb
relevant doc: nuclear weapon also known atom bomb atom bomb nuclear bomb nuclear warhead colloqui bomb nuke explos devic deriv destr
uct forc nuclear reaction either fission fission bomb combin fission fusion reaction thermonuclear bomb bomb type releas larg quanti
ti energi relat small amount matter first test fission atom bomb releas amount energi approxim equal 20 000 ton tnt 84 tj 1 first th
ermonuclear hydrogen bomb test releas energi approxim equal 10 million ton tnt 42 pj nuclear bomb yield 10 ton tnt w54 50 megaton ts
ar bomba see tnt equival thermonuclear weapon weigh littl 2 400 pound 1 100 kg releas energi equal 1 2 million ton tnt 5 0 pj 2 nucl
ear devic larger convent bomb devast entir citi blast fire radiat sinc weapon mass destruct prolifer nuclear weapon focus intern rel
at polici nuclear weapon deploy twice war unit state japanes citi hiroshima nagasaki 1945 world war ii
[1e-07, 1e-07, 1e-07, 1e-07, 1e-07, 0.0136987301369863]
```

CONCLUSION

We have seen in this project the results of our application model, so we conclude from that the Unigram for these queries is much better than the use of Bigram, as we see in the second and third queries in Bigram, the possibilities appeared in this way because the query is one word for a Bigram model, so conditions do not apply to it.

We also see that not all the results for Bigram are correct, knowing that writing the code and the query are correct, which means that spars diagram probability occurs.

Spars diagram probability means for example the probability of finding the word "python" is higher than the probability of finding a bigram "python iter".

REFERENCES

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- Geeks for geeks: https://www.geeksforgeeks.org
- Microsoft Academic : https://academic.microsoft.com