# **NLPCoursework**

March 20, 2023

```
[1]: from google.colab import drive drive.mount("/content/drive")
```

#Mount Drive

Drive already mounted at /content/drive; to attempt to forcibly remount, call drive.mount("/content/drive", force\_remount=True).

```
[2]: data_path = "/content/drive/My Drive/Colab Notebooks/COP509cw/Datasets/"
    !ls "/content/drive/My Drive/Colab Notebooks/COP509cw/Datasets/"

dataset = 'JewelleryReviewsLSA.csv'
    query = 'JewelleryReviewsQueryRelevantID.csv'
    summary = 'JewelleryReviewsSummarisationTargets.csv'
```

JewelleryReviewsLSA.csvJewelleryReviewsQueryRelevantID.gsheetJewelleryReviewsLSA.gsheetJewelleryReviewsSummarisationTargets.csvJewelleryReviewsQueryRelevantID.csv

```
[3]: import pandas as pd
import nltk;
from nltk.corpus import stopwords
import string
from collections import Counter
from nltk.tokenize import word_tokenize
nltk.download('popular')
```

```
[nltk_data] Downloading collection 'popular'
[nltk_data]
               | Downloading package cmudict to /root/nltk_data...
[nltk_data]
                   Package cmudict is already up-to-date!
[nltk_data]
[nltk_data]
               | Downloading package gazetteers to /root/nltk_data...
                   Package gazetteers is already up-to-date!
[nltk_data]
[nltk_data]
               | Downloading package genesis to /root/nltk_data...
[nltk data]
                   Package genesis is already up-to-date!
[nltk_data]
               | Downloading package gutenberg to /root/nltk_data...
[nltk_data]
                   Package gutenberg is already up-to-date!
[nltk_data]
               | Downloading package inaugural to /root/nltk_data...
```

```
[nltk_data]
                   Package inaugural is already up-to-date!
[nltk_data]
                 Downloading package movie_reviews to
[nltk_data]
                     /root/nltk_data...
[nltk_data]
               I
                   Package movie_reviews is already up-to-date!
               | Downloading package names to /root/nltk data...
[nltk data]
[nltk_data]
                   Package names is already up-to-date!
[nltk_data]
               | Downloading package shakespeare to /root/nltk data...
[nltk_data]
                   Package shakespeare is already up-to-date!
               | Downloading package stopwords to /root/nltk_data...
[nltk_data]
[nltk_data]
                   Package stopwords is already up-to-date!
[nltk_data]
               | Downloading package treebank to /root/nltk_data...
                   Package treebank is already up-to-date!
[nltk_data]
                 Downloading package twitter_samples to
[nltk_data]
[nltk_data]
                     /root/nltk_data...
[nltk_data]
                   Package twitter_samples is already up-to-date!
               | Downloading package omw to /root/nltk_data...
[nltk_data]
[nltk_data]
                   Package omw is already up-to-date!
[nltk_data]
               | Downloading package omw-1.4 to /root/nltk_data...
[nltk_data]
                   Package omw-1.4 is already up-to-date!
[nltk data]
               | Downloading package wordnet to /root/nltk data...
[nltk_data]
                   Package wordnet is already up-to-date!
               | Downloading package wordnet2021 to /root/nltk data...
[nltk_data]
[nltk_data]
                   Package wordnet2021 is already up-to-date!
[nltk_data]
               | Downloading package wordnet31 to /root/nltk_data...
[nltk_data]
                   Package wordnet31 is already up-to-date!
               | Downloading package wordnet_ic to /root/nltk_data...
[nltk_data]
                   Package wordnet_ic is already up-to-date!
[nltk_data]
[nltk_data]
               | Downloading package words to /root/nltk_data...
                   Package words is already up-to-date!
[nltk_data]
[nltk_data]
               | Downloading package maxent_ne_chunker to
[nltk_data]
                     /root/nltk_data...
                   Package maxent_ne_chunker is already up-to-date!
[nltk_data]
[nltk_data]
               | Downloading package punkt to /root/nltk_data...
[nltk_data]
                   Package punkt is already up-to-date!
[nltk data]
               | Downloading package snowball data to
[nltk_data]
               Ι
                     /root/nltk_data...
[nltk data]
                   Package snowball_data is already up-to-date!
[nltk_data]
               | Downloading package averaged_perceptron_tagger to
[nltk_data]
                     /root/nltk_data...
                   Package averaged_perceptron_tagger is already up-
[nltk_data]
[nltk_data]
                       to-date!
[nltk_data]
[nltk_data]
             Done downloading collection popular
```

[3]: True

# 1 Question 1

**Pre-process the Dataset** Load file into memory and Perform Tokenization (Word & Sentence), Stop word removal, Stemming, removal of short tokens

```
[4]: # load doc into memory
     def load doc(filename):
             # open the csv file as read into memory
             df = pd.read_csv(filename, delimiter=',', header=0)
             return df
     # turn a doc into clean tokens
     # This code was copied from - (link)
     # Source - Lab solutions for 22COP509 NLP course
     def clean_doc_vocab(doc):
             tokens = word_tokenize(doc)
             # convert to lower case
             tokens = [w.lower() for w in tokens]
             #remove duplicate words
             tokens = set(tokens)
             # remove punctuation from each token
             table = str.maketrans('', '', string.punctuation)
             tokens = [w.translate(table) for w in tokens]
             # remove remaining tokens that are not alphabetic
             tokens = [word for word in tokens if word.isalpha()]
             # filter out stop words
             stop_words = set(stopwords.words('english'))
             tokens = [w for w in tokens if not w in stop_words]
             # filter out short tokens
             tokens = [word for word in tokens if len(word) > 1]
             return tokens
     # load doc and add to vocab
     # This code was adapted from - (link)
     def add_doc_to_vocab(doc, vocab):
             # clean doc
             tokens = clean_doc_vocab(doc)
             # update counts
             vocab.update(tokens)
      # save list to file
      # # This code was copied from - [https://colab.research.google.com/drive/
      →1dTFUKVnqCJVvQckf0kbfaFNb8kK7bX5y?usp=sharing#scrollTo=NKc7lfr6D-ts]
```

```
def save_list(lines, filename):
        # convert lines to a single blob of text
        data = '\n'.join(lines)
        # open file
       file = open(filename, 'w')
        # write text
       file.write(data)
        # close file
       file.close()
def build vocab(reviews, vocab):
        # iterate through each row of the dataframe and build vocab from token
        for index, row in reviews.iterrows():
                add_doc_to_vocab(row['Reviews'], vocab)
        # keep tokens with a min occurrence - This code was copied from - (link)
       min_occurane = 2
        tokens = [k for k,c in vocab.items() if c >= min_occurane]
        # Save vocab list in a text file
       save_list(tokens, 'vocab.txt')
#Load data
data = load_doc(data_path + dataset)
# View data summary to check for possible null records
print(data.shape)
vocab = Counter()
lines = build_vocab(data, vocab)
# print the size of the vocab
print(len(vocab))
# print the top words in the vocab
print(vocab.most_common(50))
# keep tokens with a min occurrence
min occurane = 2
tokens = [k for k,c in vocab.items() if c >= min_occurane]
print(len(tokens))
# # This code block was copied from - [https://colab.research.google.com/drive/
→1dTFUKVnqCJVvQckf0kbfaFNb8kK7bX5y?usp=sharing#scrollTo=NKc7lfr6D-ts]
# load documents, clean and return line of tokens
def doc_to_line(doc, vocab):
        # clean doc
        tokens = clean_doc_vocab(doc)
        # filter by vocab
```

```
tokens = [w for w in tokens if w in vocab]
        return ' '.join(tokens)
 # load all docs in a directory
def process_docs(doc, vocab):
        lines = list()
        docs = list()
        # walk through all files
        for index, row in doc.iterrows():
                # load and clean the doc
                line = doc_to_line(row['Reviews'], vocab)
                # add to list
                lines.append(line)
                docs.append(row['Reviews'])
        return lines, docs
def read_file(doc):
  # load data
 file = open(doc,'rt')
  text = file.read()
  file.close()
  return text
```

```
(200, 3)
1090
[('ring', 105), ('like', 44), ('quality', 38), ('rings', 34), ('looks', 34),
('would', 33), ('look', 32), ('one', 32), ('wear', 32), ('picture', 32), ('nt',
31), ('beautiful', 31), ('love', 30), ('item', 26), ('great', 24), ('nice', 24),
('time', 19), ('bought', 19), ('silver', 17), ('small', 17), ('size', 16),
('got', 16), ('pretty', 16), ('price', 15), ('received', 15), ('perfect', 15),
('first', 14), ('recommend', 14), ('gift', 14), ('little', 14), ('looking', 14),
('color', 14), ('even', 13), ('really', 12), ('product', 12), ('buy', 12),
('looked', 12), ('definitely', 11), ('also', 11), ('diamond', 10), ('wedding',
10), ('seller', 10), ('diamonds', 10), ('right', 10), ('purchased', 10),
('wanted', 10), ('wearing', 10), ('much', 10), ('order', 10), ('stones', 10)]
```

### **Build Bag of Words**

```
[5]: # load the vocabulary
  vocab_filename = 'vocab.txt'
  vocab = read_file(vocab_filename)
  vocab = vocab.split()
  vocab = set(vocab)
```

```
# load all training reviews
reviews, docs = process_docs(data, vocab)
```

# 2 Question 2 - Latent Semantic Indexing (LSI)

Latent Semantic Indexing is a natural language processing technique that analyzes relationships between a set of documents and the terms they contain. Singular Value Decomposition (SVD) is used by LSI to transform the original term-document matrix into a lower-dimensional space where the relationships between terms and documents are represented as latent (hidden) concepts. This enables LSI to capture the underlying semantic meaning of words and identify related documents even when they lack many common terms. LSI has found widespread application in information retrieval, text classification, and topic modeling.

Src - Databricks Academy

# 2.1 2a - Retrieve Top 10 most similar reviews

Retrieval comprises of performing three primary steps—generate a representation of the query that specifies the information need, generate a representation of the document that captures the distribution over the information contained, and match the query and the document representations to estimate their mutual relevance.

In doing so, Document ranking is employed. This ranking typically involves a query and document representation steps, followed by a matching stage. Neural models can be useful either for generating good representations or in estimating relevance, or both.

Mitra, B. and Craswell, N. (2018) An Introduction to Neural Information Retrieval, Microsoft.com. doi: 10.1561/1500000061.

### Perform Encoding

```
[6]: from sklearn.feature extraction.text import TfidfTransformer
     from sklearn.feature extraction.text import CountVectorizer
     from sklearn.decomposition import TruncatedSVD
     from scipy.sparse import rand
     from sklearn.metrics.pairwise import cosine_similarity
     # prepare words encoding of docs - TF-IDF Approach
     # # This code block was copied from - https://colab.research.google.com/drive/
       + 1BXr4DuL - uKdQeTHUI\_jVfhyuAykrair8?usp = sharing\#scrollTo = xZk\_Cppdf0Sk
     def prepare_data(train_docs, mode, vocab):
             # encode training data set
             vectorizer = CountVectorizer(vocabulary=vocab)
             transformer = TfidfTransformer(norm='12')
             Xtrain = transformer.fit_transform(vectorizer.fit_transform(train_docs))
             return Xtrain
     # # This code block was copied from - https://colab.research.google.com/drive/
      →1qonQXIxPTDk7WUsbDQ2G7neURoWP6efH#scrollTo=HFeOO9Ca-BX-&line=12&uniqifier=1
     # preprocess query
```

```
def preprocess_query(query, mode, vocab):
    line = doc_to_line(query, vocab)
    vectorizer = CountVectorizer(vocabulary=vocab)
    transformer = TfidfTransformer(norm='12')
    encoded = transformer.fit_transform(vectorizer.fit_transform([line]))
    return encoded

Xtrain = prepare_data(reviews, 'tfidf', vocab)
    trunc_SVD_model = TruncatedSVD(n_components=5)
    approx_Xtrain = trunc_SVD_model.fit_transform(Xtrain)
    print("Approximated Xtrain shape: " + str(approx_Xtrain.shape))
```

Approximated Xtrain shape: (200, 5)

```
[7]: import numpy as np
     querys = ['The ring is a great gift. My friend loves it',
               'horrible bad quality bracelet',
               'arrived promptly and happy with the seller',
               'wear it with casual wear',
               'i expected better quality. i will return this item',
               'looks beautiful. The design is pretty. pefect and color is light',
               'This ring looks nothing like the picture. the diamonds are small and \sqcup
      ⇔not very noticeable',
               'braclet looked just like its picture and is nice quality sterling⊔
     ⇔silver.'
     ٦
     doc_ids = list()
     for index, query in enumerate(querys):
       Top_n_reviews=10
       # retrieval
       encoded_query = preprocess_query(query, 'tfidf', vocab)
       # print(encoded query.shape)
       transformed_query = trunc_SVD_model.transform(encoded_query)
       similarities = cosine_similarity(approx_Xtrain, transformed_query)
       # print("Similarities shape: " + str(similarities.shape))
       indexes = np.argsort(similarities.flat)[-Top_n_reviews:]
       doc_id = [data.iloc[indexes[i]]['ID'] for i in range(len(indexes))]
       doc_ids.append(doc_id)
       # indexes = np.argsort(similarities.flat)[::-1]
      print('_'*100)
      print(f'Query {index + 1}: {query}')
       print('='*100)
```

-----

Query 1: The ring is a great gift. My friend loves it

\_\_\_\_\_\_

\_\_\_\_\_

Top 10 documents retrieved: [9726, 2033, 26246, 41876, 17309, 35694, 17273, 44591, 36164, 49525]

Similarities scores: 0.946, 0.956, 0.96, 0.974, 0.974, 0.974, 0.979, 0.987, 0.992, 0.997

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10th Ranked result:

Doc ID: 109

A great gift to your loved one and an ever better seller. The seller deals with you in the most professional way and the security measures are superb.

Similarities: 0.9464378518512112

9th Ranked result:

Doc ID: 106

I love my birthstone and I wanted a piece of jewelry that symbolized the simple purity of the Blue Topaz. This ring did that for me. As a gift to myself for my birthday this year, it was definitely a great gift and a welcomed addition to my collection.

Similarities: 0.9562317029850116

8th Ranked result:

Doc ID: 105

This was a birthday gift for my 16 YO niece. She loves the ring and was very

happy to have received it.

Similarities: 0.9601823211536001

7th Ranked result:

Doc ID: 114

I bought this as a gift for a friends birthday and she loved it. It's a

beautifull ring.

Similarities: 0.9737436814242606

6th Ranked result:

Doc ID: 115

I always love Willow Tree. they make great gifts for great people in your life.

I have quite a collection, and I hope to continue to build it

Similarities: 0.9740717255875417

5th Ranked result:

Doc ID: 113

My neice loves her birth stone so I got it for her for a Christmas Gift. I also

love it also. great

Similarities: 0.9744105617823462

4th Ranked result:

Doc ID: 117

My mother loved this and was a great birthday gift. These look even better in person and go great with anything.

Similarities: 0.978740473935319

3th Ranked result:

Doc ID: 26

my husband loves it only thing is you cant have this ring resized due to the way

the ring is made

Similarities: 0.9870709101596368

2th Ranked result:

Doc ID: 103

I got the ring as a promise ring for  ${\tt my}$  girlfriend for  ${\tt Christmas}$  and she loved

it. Definitely a great value.

Similarities: 0.9917776235081937

1th Ranked result:

Doc ID: 111

this product made for a great gift and great memorize for my love and me. It something we will always have. a helping gift from the heart that always shows you care.

Similarities: 0.9974515774727934

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Query 2: horrible bad quality bracelet

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Top 10 documents retrieved: [4375, 10758, 1816, 265, 13373, 33571, 2114, 45548,

54748, 38305]

Similarities scores: 0.969, 0.969, 0.97, 0.97, 0.975, 0.977, 0.978, 0.985,

0.986, 0.989

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10th Ranked result:

Doc ID: 95

Very impressed with the quality of my item. Delivery was fast. Would definately

buy from this seller again

Similarities: 0.968782743270094

9th Ranked result:

Doc ID: 96

Very impressed with the quality of my item. Delivery was fast. Would definately

buy from this seller again

Similarities: 0.968782743270094

8th Ranked result:

Doc ID: 5

The quality and look were not what I had anticipated. Very flimsy. I would not

recommend this item

Similarities: 0.9695092387756503

7th Ranked result:

Doc ID: 6

The quality of this item was not up to expectations. The Top was scratched, the hinges did not line up to the pre-drilled holes and the staining was

inconsistant. If I saw this item in a store I would not have purchased it.

Similarities: 0.969746395060482

6th Ranked result:

Doc ID: 153

The item was not as pictured. It is funky and of poor quality. The seller did not respond when I contacted him about this.

Similarities: 0.9746027268592024

### 5th Ranked result:

Doc ID: 157

The item was misrepresented. Size and quality were horrible. I would return this item except family member is in the Coast Guard and it was sent to him. A total waste of money.

Similarities: 0.9770901004181627

#### 4th Ranked result:

Doc ID: 123

The stones on this bracelet are extremely pale, more pink than purple. I ended up returning the bracelet because I have amethyst jewelry and it was extremely poor quality.

Similarities: 0.9778037962243905

#### 3th Ranked result:

Doc ID: 41

This is an attractive and high quality item for a young teenager. It is too small for an adult.

Similarities: 0.9854028356895472

### 2th Ranked result:

Doc ID: 156

Item arrived extremely damaged in several places. Not packaged well had to send it back. Very disappointed with the quality.

Similarities: 0.986475933460864

### 1th Ranked result:

Doc ID: 99

The flute charm is so detailed and is of very high quality. You can see all the keys, any flute fan would adore having this item.

Similarities: 0.9886809098399278

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Query 3: arrived promptly and happy with the seller

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Top 10 documents retrieved: [8110, 27679, 10758, 4375, 29722, 41889, 19944, 49216, 33251, 22058]

Similarities scores: 0.963, 0.964, 0.965, 0.965, 0.97, 0.971, 0.973, 0.975,

0.992, 0.995

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#### \_\_\_\_\_

#### 10th Ranked result:

Doc ID: 93

I was very pleased with the quality of this item. Will definately reccommend Eve's Addiction to all my friends and family.

Similarities: 0.9629886314217946

#### 9th Ranked result:

Doc ID: 128

Item was shipped and received within the time limit given. Good quality product t t t t t t  $\!\!$ 

Similarities: 0.9642036333457844

### 8th Ranked result:

Doc ID: 96

Very impressed with the quality of my item. Delivery was fast. Would definately buy from this seller again

Similarities: 0.9653794089864282

#### 7th Ranked result:

Doc ID: 95

Very impressed with the quality of my item. Delivery was fast. Would definately

buy from this seller again

Similarities: 0.9653794089864282

#### 6th Ranked result:

Doc ID: 131

I received this Italian horn in pristine condition and I was completely satisfied with the receiving of this product in a timely manner.

Similarities: 0.969525302112588

### 5th Ranked result:

Doc ID: 97

I was very impressed with the quality and would not hesitate to purchase other items from the Seller. Their service was also exceptional.

Similarities: 0.9705996254909582

4th Ranked result:

Doc ID: 135

am very pleased with my purchase, speedy shipping will use again

Similarities: 0.972971925549139

3th Ranked result:

Doc ID: 138

My item came quickly and in plenty of time for Christmas. They were a huge hit

with the person who received them Similarities: 0.9745706640774308

2th Ranked result:

Doc ID: 125

I am happy with the product, I received it as advertised and in a timely manner; seller/Amazon kept me updated about shipment/delivery status. Would recommend item and seller

Similarities: 0.9922734132101019

1th Ranked result:

Doc ID: 100

Item was great quality and came promptly. I'm very happy with it and recommend it unreservedly.

Similarities: 0.9952969379133926

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Query 4: wear it with casual wear

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Top 10 documents retrieved: [12483, 2131, 44126, 2134, 11087, 28648, 37486,

36585, 535, 19852]

Similarities scores: 0.952, 0.953, 0.975, 0.976, 0.978, 0.979, 0.985, 0.985,

0.99, 0.991

\_\_\_\_\_\_

10th Ranked result:

Doc ID: 28

They definitely help lessen your appitite, however my ears were sore after wearing for about 3 hours and the next few days I tried to wear them off and on and to increase the wearing time. If you have a good pain tolerance you may not notice any discomfort, as for me my ears lobes were swollen and I had to stop wearing them for 4 days.

Similarities: 0.952412407045051

### 9th Ranked result:

Doc ID: 143

I wanted a classy piece to wear on my right hand for work when I'm wearing Gold. I found that I will end up wearing this outside of work. Very classy looking

Similarities: 0.9525631226554471

### 8th Ranked result:

Doc ID: 152

It is so unique and a pleasure to wear. The stones catch the light and the style is very comfortable to wear.

Similarities: 0.9745112039331063

### 7th Ranked result:

Doc ID: 145

ery suitable for wearing for fashionable occasions. very dressy

Similarities: 0.9755194862953138

#### 6th Ranked result:

Doc ID: 13

its what i wanted :) but its not my favorite piercing of mine but i have to wear

the bioplast cuz i break out with certain metals

Similarities: 0.9779021063838653

#### 5th Ranked result:

Doc ID: 140

The days I do not wear the blue one I wear this one. I really enjoy wearing

something Celtic and pretty.

Similarities: 0.9788447604217865

### 4th Ranked result:

Doc ID: 141

This pendant I classify as the best for casual wear. I wear on the weekends or out & about but isn't not suited for my work or my going out events

Similarities: 0.984803415218609

### 3th Ranked result:

Doc ID: 146

I am looking forward to wearing them as they sparkle and catch every eye at my son's wedding on June 30

Similarities: 0.9853059829648068

2th Ranked result:

Doc ID: 14

It serves the purpose, but it seemed to me that the image was a lot prettier and sparklier than it turned out to be. I wear it UNDER my shirt since it does not compliment anything I wear.

Similarities: 0.9899723875818819

1th Ranked result:

Doc ID: 144

very good for everyday wear or dressing up

Similarities: 0.9910997079537142

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Query 5: i expected better quality. i will return this item

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\_\_\_\_\_

Top 10 documents retrieved: [1816, 33571, 41889, 8110, 45548, 4375, 10758,

13373, 54748, 38305]

Similarities scores: 0.986, 0.986, 0.986, 0.991, 0.991, 0.991, 0.991, 0.994,

0.995, 0.997

\_\_\_\_\_\_

\_\_\_\_\_

10th Ranked result:

Doc ID: 5

The quality and look were not what I had anticipated. Very flimsy. I would not

recommend this item

Similarities: 0.9856629268895757

9th Ranked result:

Doc ID: 157

The item was misrepresented. Size and quality were horrible. I would return this item except family member is in the Coast Guard and it was sent to him. A total waste of money.

Similarities: 0.9861474694462455

8th Ranked result:

Doc ID: 97

I was very impressed with the quality and would not hesitate to purchase other items from the Seller. Their service was also exceptional.

Similarities: 0.9863031564674286

### 7th Ranked result:

Doc ID: 93

I was very pleased with the quality of this item. Will definately reccommend

Eve's Addiction to all my friends and family.

Similarities: 0.9906267947437524

### 6th Ranked result:

Doc ID: 41

This is an attractive and high quality item for a young teenager. It is too small for an adult.

Similarities: 0.9912410103121873

### 5th Ranked result:

Doc ID: 95

Very impressed with the quality of my item. Delivery was fast. Would definately

buy from this seller again

Similarities: 0.9913698416482508

### 4th Ranked result:

Doc ID: 96

Very impressed with the quality of my item. Delivery was fast. Would definately

buy from this seller again

Similarities: 0.9913698416482508

#### 3th Ranked result:

Doc ID: 153

The item was not as pictured. It is funky and of poor quality. The seller did not respond when I contacted him about this.

Similarities: 0.9936487737696234

### 2th Ranked result:

Doc ID: 156

Item arrived extremely damaged in several places. Not packaged well had to send it back. Very disappointed with the quality.

Similarities: 0.9952076037825203

### 1th Ranked result:

Doc ID: 99

The flute charm is so detailed and is of very high quality. You can see all the

keys, any flute fan would adore having this item.

Similarities: 0.9972884321243866

\_\_\_\_\_

Query 6: looks beautiful. The design is pretty. pefect and color is light

\_\_\_\_\_

Top 10 documents retrieved: [43945, 27474, 12358, 32767, 28543, 42077, 46500, 41319, 39932, 45860]

Similarities scores: 0.924, 0.924, 0.927, 0.93, 0.93, 0.957, 0.962, 0.969, 0.971, 0.976

\_\_\_\_\_\_

#### \_\_\_\_\_

#### 10th Ranked result:

Doc ID: 161

The diamond looks pretty big. For the price, it shines brilliantly. The color doesn't look very white though. But you don't expect K color to be very white. Overall, I think it's pretty. and I am very happy with it.

Similarities: 0.9239421100333045

### 9th Ranked result:

Doc ID: 160

The diamond looks pretty big. For the price, it shines brilliantly. The color doesn't look very white though. But you don't expect K color to be very white. Overall, I think it's pretty. and I am very happy with it.

Similarities: 0.9239421100333045

### 8th Ranked result:

Doc ID: 163

These look quite like their photograph. They are very colorful and you know they are turtles. I've seen them elsewhere for quite a high price and these are beautiful.

Similarities: 0.9271019179717989

### 7th Ranked result:

Doc ID: 0

i expect like regular size of ring, but this one look like a ring for toy or something funy, the MM of our rings is 5MM and this ring may be is 1MMso ridiculousMartin1/5 ct.tw Round Diamond Solitaire Ring in 18k White Gold Similarities: 0.9301791849721579

#### 6th Ranked result:

Doc ID: 192

The diamond had a crack in one Garnet and another one had a large chip.

Similarities: 0.9304106264859551

### 5th Ranked result:

Doc ID: 45

This is a solid.beautiful ring. But if you are expecting the color in rhe picture you will be disappointed. It is barely pink at all. When I first saw it I thought it was lavendar. It's still pretty but buy for design not color. Similarities: 0.9567885798390113

#### 4th Ranked result:

Doc ID: 159

The Earrings you sent me are real light in color not the pretty dark color you show in the picture. They look almost light pink. I will keep them they are also pretty but not what I expected.

Similarities: 0.9619529234838238

#### 3th Ranked result:

Doc ID: 164

The ring is exactly as pictured and looks very pretty on my hand. The color of the stones is rich and beautiful.

Similarities: 0.969096685207524

### 2th Ranked result:

Doc ID: 165

This dainty heart looks absolutely beautiful on. It picks up the colors of your clothing. It is an amazing price for such a beautiful pendant.

Similarities: 0.9706493608870369

# 1th Ranked result:

Doc ID: 158

This is one of the most beautiful rosarys I have seen. The smoothness and color of the beads is so translucent looking that it almost looks like glass. The workmanship is excellent and the details are beautiful. A truly beautiful piece to own.

Similarities: 0.9756106120431935

-----

Query 7: This ring looks nothing like the picture. the diamonds are small and

### not very noticeable

\_\_\_\_\_

#### \_\_\_\_\_

Top 10 documents retrieved: [3494, 11356, 28542, 37864, 6649, 47345, 943,

41872, 38637, 209]

Similarities scores: 0.954, 0.958, 0.967, 0.973, 0.977, 0.978, 0.987, 0.987,

0.989, 0.992

-----

#### ===========

### 10th Ranked result:

Doc ID: 188

It is as nice as it looks on the picture. :) I like it. :)

Similarities: 0.954007201382691

#### 9th Ranked result:

Doc ID: 174

Although the picture shows a cute looking ring this ring isn't pretty. The fringed look, only looks like the ring has been left on the floor and someone ran it over with a vaccum cleaner.

Similarities: 0.9581234351658509

### 8th Ranked result:

Doc ID: 171

The ring was nice and looked like picture but had a crack in one Garnet and another one had a large chip.

Similarities: 0.9670399912352006

#### 7th Ranked result:

Doc ID: 183

I fell in love with the picture. The ring showed to be sligthly brushed looking. When the ring arrived I was quick to learn the picture looks nothing like the ring. The ring is a bright polish and the yellow gold is barely visiable. I'm very disappointed with amazon for the lack of description.

Similarities: 0.9727204399650787

### 6th Ranked result:

Doc ID: 178

I received my ring and was a little disappointed that the ring is not completely blue (like the picture shows). It looks like I got a blue flower with green leaves. So it makes the ring look blue and green. Very small ring. Not worth \$6.99 but more like \$3.

Similarities: 0.9765844015019487

5th Ranked result:

Doc ID: 173

I didn't like this product because the diamonds looked nothing like the picture.

The diamonds are flawed more than a little bit.

Similarities: 0.9780401549362725

4th Ranked result:

Doc ID: 182

It looks like a ring for a man when you look at the picture online, but in real

life its a very feminine looking ring.

Similarities: 0.9868370605925979

3th Ranked result:

Doc ID: 191

Looked just as well as the picture does. Only thing i could say is that it is a little more polished than it looks like and the black stands out which looks very nice.

Similarities: 0.9873913912702579

2th Ranked result:

Doc ID: 176

I was a little disappointed when I received my ring in the mail. In the picture provided above the sides look like they make a heart shape, or at least it looks like smooth, clean curved lines. The ring I got in the mail looks like the sides are smushed in and not clean curves. Other then that I like it. I just wished it looked like the picture.

Similarities: 0.9886068639154282

1th Ranked result:

Doc ID: 170

This ring looks nothing like the picture. the diamonds are small and not very

noticeable; I will be sending this back

Similarities: 0.9923302665020217

-----

Query 8: braclet looked just like its picture and is nice quality sterling

\_\_\_\_\_\_

-----

Top 10 documents retrieved: [47345, 41872, 735, 10642, 3494, 53409, 44490, 45518, 56865, 642]

Similarities scores: 0.926, 0.932, 0.94, 0.941, 0.948, 0.968, 0.98, 0.988,

0.988, 0.999

\_\_\_\_\_\_

#### \_\_\_\_\_\_

#### 10th Ranked result:

Doc ID: 173

I didn't like this product because the diamonds looked nothing like the picture.

The diamonds are flawed more than a little bit.

Similarities: 0.9256913540974214

### 9th Ranked result:

Doc ID: 191

Looked just as well as the picture does. Only thing i could say is that it is a little more polished than it looks like and the black stands out which looks very nice.

Similarities: 0.9319192802062732

### 8th Ranked result:

Doc ID: 189

This is a perfect size solid charm that looks the same on either side. Silver is nicely finished and the enamel is a nice highlight. Really looks like the picture.

Similarities: 0.9401247764332208

#### 7th Ranked result:

Doc ID: 185

From the picture they looked to have some purple in them but they are clear just

like the title says.

Similarities: 0.9413515984537485

#### 6th Ranked result:

Doc ID: 188

It is as nice as it looks on the picture. :) I like it. :)

Similarities: 0.9477428350411371

### 5th Ranked result:

Doc ID: 193

Although the picture looks like metal beads and description states sterling silver, these are pearls.

Similarities: 0.967850835704277

# 4th Ranked result: Doc ID: 196 These are very good quality. They are light weight and nice small size. Just as described. They look like the picture. Similarities: 0.9801763182326474 3th Ranked result: Doc ID: 187 It was much smaller than it looked like in the picture and the silver necklace seemed to be of poorer quality than expected. Similarities: 0.9880931102532827 2th Ranked result: Doc ID: 194 Looks exactly like the picture. Very nice quality. A must for everyone who is a Tiger fan and owns an Italian Charm Bracelet. Similarities: 0.988340741702246 1th Ranked result: Doc ID: 184 This medical alert braclet looked just like its picture and is nice quality sterling silver. Similarities: 0.9994153382721591

Define functions for Emperical tuning of Weighting schemes

```
# prepare words encoding of docs - Training emperically
# # This code block was copied from - https://colab.research.google.com/drive/
→1BXr4DuL-uKdQeTHUI_jVfhyuAykrair8?usp=sharing#scrollTo=xZk_Cppdf0Sk
def _prepare_data(train_docs, mode, vocab):
 # Tune the LSI model
 if mode == 'tfidf':
    encoded = prepare_data(train_docs, mode, vocab)
 if mode == 'binary':
   transformer = CountVectorizer(vocabulary=vocab, binary=True)
 if mode == 'count':
   transformer = CountVectorizer(vocabulary=vocab)
 if mode == 'tf':
    encoded = prepare_tf_data(train_docs, mode, vocab)
 return encoded
# # This code block was copied from - https://colab.research.google.com/drive/
 →1qonQXIxPTDk7WUsbDQ2G7neURoWP6efH#scrollTo=HFeOO9Ca-BX-&line=12&uniqifier=1
# preprocess query
def _preprocess_query(query, mode, vocab):
 line = doc_to_line(query, vocab)
  # Tune the LSI model
  # for scheme in weighting_schemes:
 if mode == 'tfidf':
   transformed = preprocess_query(query, mode, vocab)
 if mode == 'binary':
    transformed = CountVectorizer(vocabulary=vocab, binary=True)
 if mode == 'count':
    transformed = CountVectorizer(vocabulary=vocab)
 if mode == 'tf':
   transformed = preprocess_tf_query(query, mode, vocab)
 return transformed
Xtrain = _prepare_data(reviews, 'tfidf', vocab)
trunc_SVD_model = TruncatedSVD(n_components=5)
approx_Xtrain = trunc_SVD_model.fit_transform(Xtrain)
# print("Approximated Xtrain shape: " + str(approx Xtrain.shape))
```

## 2.2 2b - Emperically Tune the LSI model

### **Define Evaluation Metrics**

```
[9]: # Interplot Precision for standard Recall
def InterplotPrecision(p=0.1, Precision=None, Recall=None):
    if p >= 1.0:
```

```
p = 0.9
   Mark = np.zeros(2)
   1 = 0
   r = 0
   for i in range(len(Recall)):
       if Recall[i] >= p and Mark[0] == 0:
           1 = i
           Mark[0] = 1
       if Recall[i] >= p + 0.1 and Mark[1] == 0:
       # if Recall[i] >= 1.0 and Mark[1] == 0:
           r = i
           Mark[1] = 1
   y = max(Precision[1:(r+1)])
   return y
# obtain y axis for R/P curve
def compute_RP_yaxis(Precision=None, Recall=None):
 for i in range(11):
   pInput = 0.1 * i
   y_axis[i] = InterplotPrecision(p=pInput, Precision=Precision, Recall=Recall)
 return y_axis
# compute Recall, Precision, F1-measure
def compute_R_P_F1(re_mark=None, QuRe_ID =None):
 Recall = []
 Precision = []
 F1measure = []
 for i in range(len(re_mark)):
   r = sum(re_mark[:(i+1)])
   Re = r/(len(QuRe_ID))
   Pr = r/(i+1)
   # avoid divisor to be 0
   FD = Re + Pr
   if FD == 0:
     FD=1
   F1 = 2*Re*Pr/FD
   Recall.append(Re)
   Precision.append(Pr)
   F1measure.append(F1)
 return Recall, Precision, F1measure
```

### 2.2.1 Evaluate LSI models

Deprecated LSI

```
[10]: Xtrain = _prepare_data(reviews, 'tf', vocab)
      trunc_SVD_model = TruncatedSVD(n_components=5)
      approx_Xtrain = trunc_SVD_model.fit_transform(Xtrain)
      re_ID =
       →[[36164,58481,26246,2033,48779,34523,9726,56494,49525,45278,35694,41876,17309,11135,17273,1
               [57123,25299,55017,7432,2114,40871],
       4 [33251,17304,50019,27679,6158,22408,29722,36677,2780,17944,19944,31657,52867,49216],
       40373,28648,37486,30640,2131,19852,2134,36585,26535,51474,21070,56330,53660,44126],
               [13373,17607,41459,54748,33571],
       45860,46500,27474,43945,52837,12358,41319,39932,45146,50197,8341,52375],

    [209,28542,216,47345,11356,33632,38637,7110,6649,51356,44358,36165,943,37864],

       [642,10642,37794,45518,3494,735,10037,41872,28542,53409,56865,44489,44490]]
      AllRecall = list()
      AllPrecision = list()
      AllF1measure = list()
      _y_axis_lsi_tf = list()
      _y_axis_lsi_tfidf = list()
      # loop queries
      j = 0
      for query in querys:
        # retrieval
        encoded_query = _preprocess_query(query, 'tf', vocab)
        transformed_query = trunc_SVD_model.transform(encoded_query)
        similarities = cosine_similarity(approx_Xtrain, transformed_query)
        # rank the index
        indexes = np.argsort(similarities.flat)[::-1]
        doc_id = [data.iloc[indexes[i]]['ID'] for i in range(len(indexes))]
        # Mark the relevant index
        re mark = []
        for i in range(len(indexes)):
          if (doc_id[i]) in re_ID[j]:
           re_mark.append(1)
          else:
            re_mark.append(0)
        # print(re_mark)
        # compute Recall, Precision, F1-measure
```

```
Recall, Precision, F1measure = compute_R_P_F1(re_mark=re_mark,_

QuRe_ID=re_ID[j])
 print('\n' + 'Query%d: '%(j+1) + query)
 # for i in range(10):
  # print("Top " + str(i+1) + ' result: ID%d '%(indexes[i]+1),
 → ArRe train lines[indexes[i]])
 Recall = np.array(Recall)
 Precision = np.array(Precision)
 F1measure = np.array(F1measure)
  # print(re_mark)
 print("Recall@1~10: ", np.around(Recall[:10],2))
 print("Precision@1~10: ", np.around(Precision[:10],2))
 print("F1measure@1~10: ", np.around(F1measure[:10],2))
  # save
 AllRecall.append(Recall)
 AllPrecision.append(Precision)
 AllF1measure.append(F1measure)
  # plot R/P curve
 x_axis = [0.0, 0.1, 0.2, 0.3, 0.4, 0.5, 0.6, 0.7, 0.8, 0.9, 1.0]
 y_axis = compute_RP_yaxis(Precision=Precision, Recall=Recall)
 _y_axis_lsi_tfidf.append(y_axis)
 plt.plot(x_axis, y_axis, '-bo', color="purple", label="Query%d"%(j+1))
 plt.xlim(0, 1)
 plt.ylim(0, 1)
 plt.xlabel('Recall')
 plt.ylabel('Precision')
 plt.title('Standard Recall/Precision Curves')
 plt.legend()
 plt.show()
 j += 1
# compute average Recall, average Precision, average F1-measure
AllRecall = np.array(AllRecall)
AllPrecision = np.array(AllPrecision)
AllF1measure = np.array(AllF1measure)
AveRecall = (AllRecall[0] + AllRecall[1] + AllRecall[2] + AllRecall[3] +
 AllRecall[4] + AllRecall[5] + AllRecall[6] + AllRecall[7])/8
AvePrecision = (AllPrecision[0] + AllPrecision[1]+AllPrecision[2] +
 AllPrecision[3]+AllPrecision[4] + AllPrecision[5] + AllPrecision[6] +
 →AllPrecision[7])/8
AveF1measure = (AllF1measure[0] + AllF1measure[1] + AllF1measure[2] + __
 AllF1measure[3]+AllF1measure[4] + AllF1measure[5] + AllF1measure[6] +
 →AllF1measure[7])/8
```

```
print("\nAverage Recall, average Precision, average F1-measure: ")
print("average Recall@1~10: ", np.around(AveRecall[:10],2))
print("average Precision@1~10: ", np.around(AvePrecision[:10],2))
print("average F1measure01~10: ", np.around(AveF1measure[:10],2))
# plot average R/P curve
x_axis = [0.0, 0.1, 0.2, 0.3, 0.4, 0.5, 0.6, 0.7, 0.8, 0.9, 1.0]
y_axis = compute_RP_yaxis(Precision=AvePrecision, Recall=AveRecall)
plt.plot(x_axis, y_axis, '-bo', color="blue", label="Average")
plt.xlim(0, 1)
plt.ylim(0, 1)
plt.xlabel('average Recall')
plt.ylabel('average Precision')
plt.title('Standard Average Recall/Precision Curves')
plt.legend()
plt.show()
LSI_y_axis_avg = y_axis
```

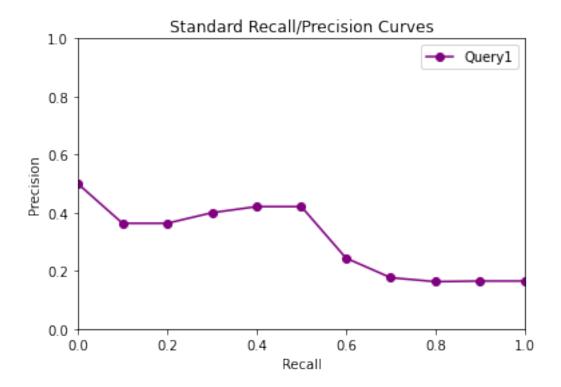
```
Query1: The ring is a great gift. My friend loves it

Recall@1~10: [0. 0.06 0.06 0.06 0.06 0.06 0.12 0.12 0.19 0.19]

Precision@1~10: [0. 0.5 0.33 0.25 0.2 0.17 0.29 0.25 0.33 0.3 ]

Fimeasure@1~10: [0. 0.11 0.11 0.1 0.09 0.17 0.17 0.24 0.23]

<ipython-input-10-1e3085a49a4c>:64: UserWarning: color is redundantly defined by the 'color' keyword argument and the fmt string "-bo" (-> color='b'). The keyword argument will take precedence.
```

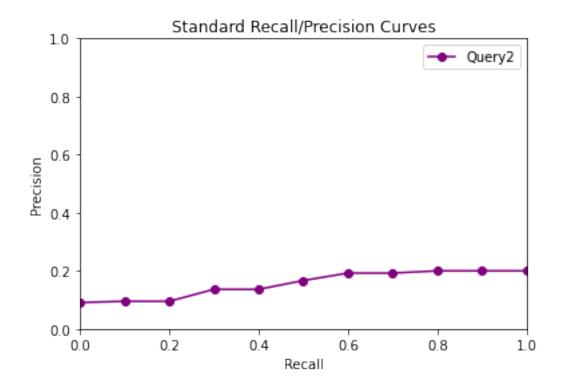


```
Query2: horrible bad quality bracelet Recall@1~10: [0. 0. 0. 0. 0. 0. 0. 0. 0. 0.]
```

Precision@1~10: [0. 0. 0. 0. 0. 0. 0. 0. 0.]

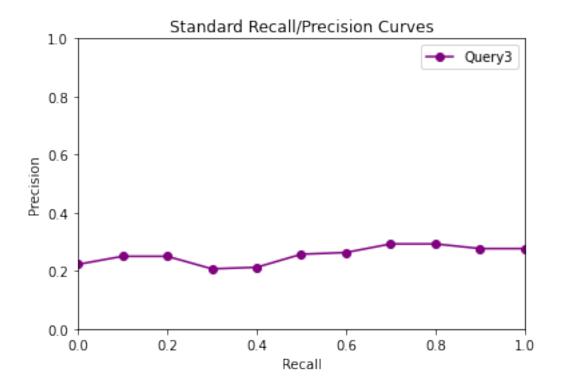
F1measure@1~10: [0. 0. 0. 0. 0. 0. 0. 0. 0. 0.]

<ipython-input-10-1e3085a49a4c>:64: UserWarning: color is redundantly defined by
the 'color' keyword argument and the fmt string "-bo" (-> color='b'). The
keyword argument will take precedence.



Query3: arrived promptly and happy with the seller Recall@1~10: [0. 0. 0. 0. 0.07 0.07 0.07 0.14 0.14] Precision@1~10: 0.17 0.14 0.12 0.22 0.2 ] [0. 0. 0. 0. 0. F1measure@1~10: [0. 0.1 0.1 0.09 0.17 0.17] 0. 0. 0. 0.

<ipython-input-10-1e3085a49a4c>:64: UserWarning: color is redundantly defined by
the 'color' keyword argument and the fmt string "-bo" (-> color='b'). The
keyword argument will take precedence.

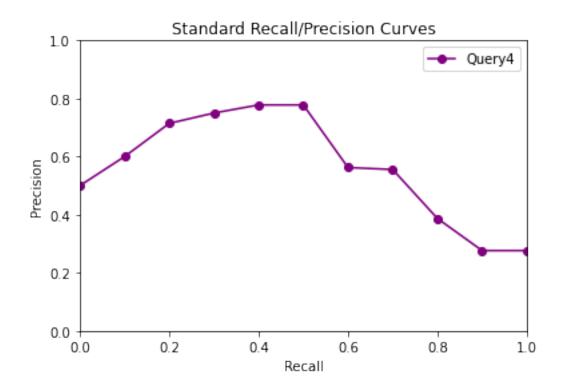


Query4: wear it with casual wear

Recall@1~10: [0. 0.07 0.07 0.14 0.21 0.29 0.36 0.43 0.5 0.5]

Precision@1~10: [0. 0.5 0.33 0.5 0.6 0.67 0.71 0.75 0.78 0.7 ]
F1measure@1~10: [0. 0.12 0.12 0.22 0.32 0.4 0.48 0.55 0.61 0.58]

<ipython-input-10-1e3085a49a4c>:64: UserWarning: color is redundantly defined by
the 'color' keyword argument and the fmt string "-bo" (-> color='b'). The
keyword argument will take precedence.



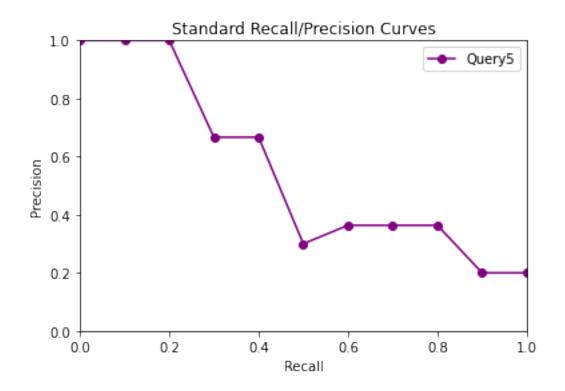
Query5: i expected better quality. i will return this item

Recall@1~10: [0.2 0.2 0.4 0.4 0.4 0.4 0.4 0.4 0.4 0.6]

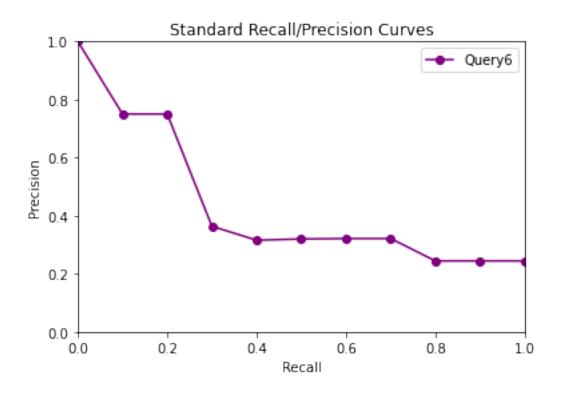
Precision@1~10: [1. 0.5 0.67 0.5 0.4 0.33 0.29 0.25 0.22 0.3 ]

F1measure@1~10: [0.33 0.29 0.5 0.44 0.4 0.36 0.33 0.31 0.29 0.4 ]

<ipython-input-10-1e3085a49a4c>:64: UserWarning: color is redundantly defined by
the 'color' keyword argument and the fmt string "-bo" (-> color='b'). The
keyword argument will take precedence.



<ipython-input-10-1e3085a49a4c>:64: UserWarning: color is redundantly defined by
the 'color' keyword argument and the fmt string "-bo" (-> color='b'). The
keyword argument will take precedence.



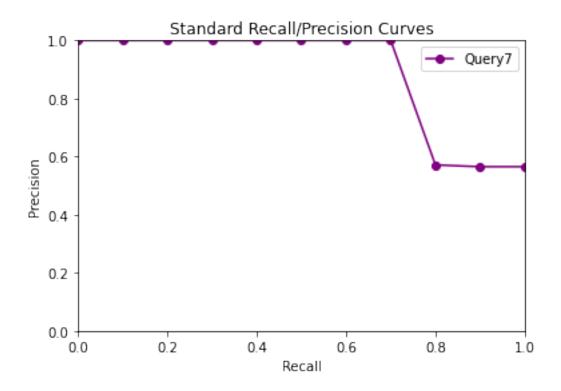
Query7: This ring looks nothing like the picture. the diamonds are small and not very noticeable

Recall@1~10: [0.07 0.14 0.21 0.29 0.36 0.43 0.5 0.57 0.64 0.71]

Precision@1~10: [1. 1. 1. 1. 1. 1. 1. 1. 1.]

F1measure@1~10: [0.13 0.25 0.35 0.44 0.53 0.6 0.67 0.73 0.78 0.83]

<ipython-input-10-1e3085a49a4c>:64: UserWarning: color is redundantly defined by
the 'color' keyword argument and the fmt string "-bo" (-> color='b'). The
keyword argument will take precedence.

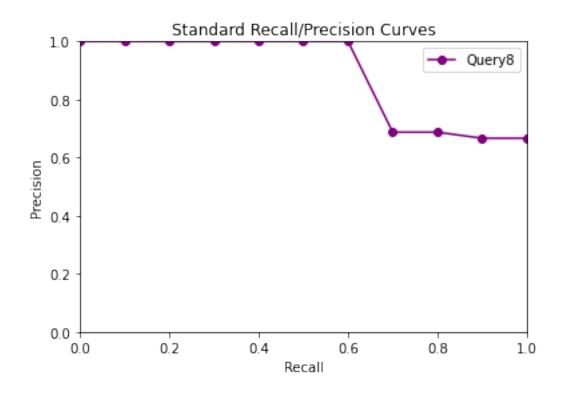


<ipython-input-10-1e3085a49a4c>:64: UserWarning: color is redundantly defined by
the 'color' keyword argument and the fmt string "-bo" (-> color='b'). The
keyword argument will take precedence.

plt.plot(x\_axis, y\_axis, '-bo', color="purple", label="Query%d"%(j+1))

Query8: braclet looked just like its picture and is nice quality sterling silver.

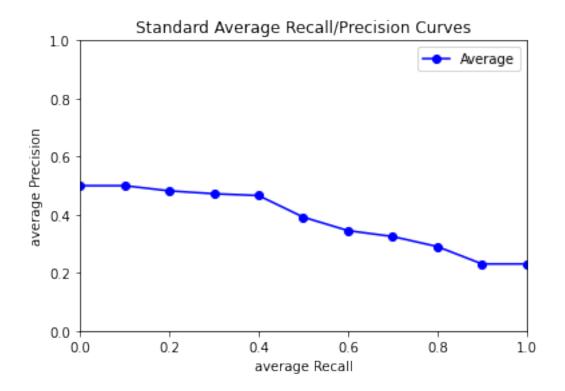
F1measure@1~10: [0.14 0.27 0.38 0.47 0.56 0.63 0.7 0.76 0.73 0.7]



Average Recall, average Precision, average F1-measure: average Recall@1~10: [0.05 0.09 0.14 0.18 0.21 0.24 0.28 0.31 0.34 0.38] average Precision@1~10: [0.5 0.5 0.5 0.5 0.48 0.48 0.48 0.47 0.47 0.45] average F1measure@1~10: [0.1 0.15 0.21 0.26 0.28 0.31 0.35 0.36 0.39 0.4]

<ipython-input-10-1e3085a49a4c>:91: UserWarning: color is redundantly defined by
the 'color' keyword argument and the fmt string "-bo" (-> color='b'). The
keyword argument will take precedence.

plt.plot(x\_axis, y\_axis, '-bo', color="blue", label="Average")



### Adapted LSI implementation

```
Tune with TFIDF and SVD dimension of 5
```

```
[11]: import warnings
      warnings.filterwarnings('ignore')
      # !pip install prettytable
      from prettytable import PrettyTable
      # Plot table
      def plot_df_table(result):
       pt = PrettyTable()
        # Add columns to the PrettyTable
       pt.field_names = ["Query", "Recall@1~10", "Precision@1~10", "F1measure@1~10"]
        # Add rows from results to the table
        for index, row in result.iterrows():
          pt.add_row([row['Query'], row['Recall@1~10'], row['Precision@1~10'],__
       →row['F1measure@1~10']])
       print(pt)
        # Plot table
      def plot_avg_table(result):
        pt = PrettyTable()
```

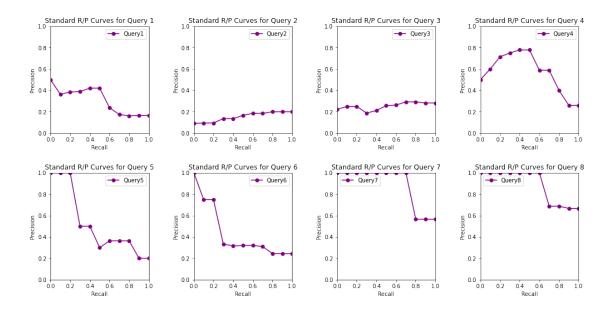
```
# Add columns to the PrettyTable
 pt.field_names = ['Query', 'Average Recall@1~10', 'Average Precision@1~10', "
 # Add rows from results to the table
 for index, row in result.iterrows():
   pt.add_row([index+1, row['Average Recall@1~10'], row['Average_
 ⇔Precision@1~10'], row['Average F1measure@1~10']])
 print(pt)
# Define tuning parameters for weighthing schemes and SVD parameters
Xtrain = prepare data(reviews, 'tf', vocab)
trunc_SVD_model = TruncatedSVD(n_components=5)
approx_Xtrain = trunc_SVD_model.fit_transform(Xtrain)
re_ID =
 →[[36164,58481,26246,2033,48779,34523,9726,56494,49525,45278,35694,41876,17309,11135,17273,1
         [57123,25299,55017,7432,2114,40871],
 4[33251,17304,50019,27679,6158,22408,29722,36677,2780,17944,19944,31657,52867,4\\(\frac{1}{2}\)16],
 40373,28648,37486,30640,2131,19852,2134,36585,26535,51474,21070,56330,53660,44126],
         [13373,17607,41459,54748,33571],
 45860,46500,27474,43945,52837,12358,41319,39932,45146,50197,8341,52375],
 [209,28542,216,47345,11356,33632,38637,7110,6649,51356,44358,36165,943,37864]
 -[642,10642,37794,45518,3494,735,10037,41872,28542,53409,56865,44489,44490]]
AllRecall = list()
AllPrecision = list()
AllF1measure = list()
_y_axis_lsi_tf = list()
_y_axis_lsi_tfidf = list()
# Create a figure with subplots
fig, axes = plt.subplots(2, 4, figsize=(15, 8))
fig.tight_layout(pad=5.0)
axes = axes.ravel()
# Create an empty DataFrame to store results
results_df = pd.DataFrame(columns=['Query', 'Recall01~10', 'Precision01~10', \_
```

```
# loop queries
j = 0
for query in querys:
  # retrieval
  encoded_query = _preprocess_query(query, 'tfidf', vocab)
  transformed_query = trunc_SVD_model.transform(encoded_query)
  similarities = cosine_similarity(approx_Xtrain, transformed_query)
  # rank the index
  indexes = np.argsort(similarities.flat)[::-1]
  doc_id = [data.iloc[indexes[i]]['ID'] for i in range(len(indexes))]
  # Mark the relevant index
 re_mark = []
  for i in range(len(indexes)):
    if (doc_id[i]) in re_ID[j]:
     re_mark.append(1)
    else:
     re_mark.append(0)
  # print(re_mark)
  # compute Recall, Precision, F1-measure
 Recall, Precision, F1measure = compute_R_P_F1(re_mark=re_mark,__
 →QuRe ID=re ID[j])
  # Save the results in the DataFrame
  results_df.loc[j] = [f"Query{j+1}", np.around(Recall[:10], 2), np.
 →around(Precision[:10], 2), np.around(F1measure[:10], 2)]
  # save
 AllRecall.append(Recall)
  AllPrecision.append(Precision)
  AllF1measure.append(F1measure)
  # Plot R/P curve in the subplot
  x_axis = np.linspace(0, 1, 11)
 y_axis = compute_RP_yaxis(Precision=Precision, Recall=Recall)
  _y_axis_lsi_tfidf.append(y_axis)
  axes[j].plot(x_axis, y_axis, '-bo', color="purple", label="Query%d" % (j + 1))
  axes[j].set_xlim(0, 1)
  axes[j].set_ylim(0, 1)
  axes[j].set_xlabel('Recall')
  axes[j].set_ylabel('Precision')
  axes[j].set_title(f'Standard R/P Curves for Query {j + 1}')
  axes[j].legend()
  j += 1
```

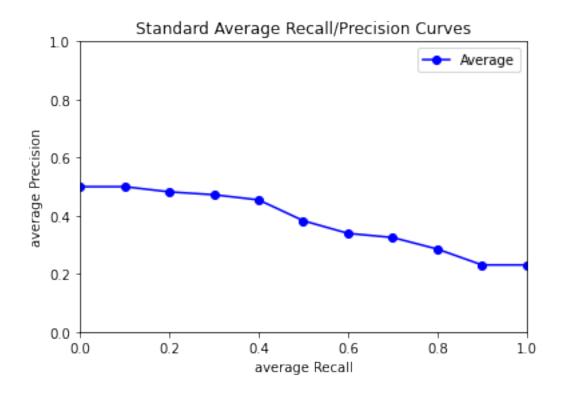
```
# Print the results in a formatted table
print("\nResults for top n docs returned for each query:")
plot_df_table(results_df)
# Show the subplots
plt.show()
# print(results_df)
# compute average Recall, average Precision, average F1-measure
AllRecall = np.array(AllRecall)
AllPrecision = np.array(AllPrecision)
AllF1measure = np.array(AllF1measure)
AveRecall = (AllRecall[0] + AllRecall[1] + AllRecall[2] + AllRecall[3] +
 AllRecall[4] + AllRecall[5] + AllRecall[6] + AllRecall[7])/8
AvePrecision = (AllPrecision[0] + AllPrecision[1]+AllPrecision[2] +
 AllPrecision[3]+AllPrecision[4] + AllPrecision[5] + AllPrecision[6] +
 →AllPrecision[7])/8
AveF1measure = (AllF1measure[0] + AllF1measure[1]+AllF1measure[2] +
 AllF1measure[3]+AllF1measure[4] + AllF1measure[5] + AllF1measure[6] +
 →AllF1measure[7])/8
# Create a DataFrame for average results
avg_results_df = pd.DataFrame({'Average Recall@1~10': np.around(AveRecall[10:],__
 ⇒2).
                                'Average Precision@1~10': np.
 ⇒around(AvePrecision[10:], 2),
                                'Average F1measure@1~10': np.
 →around(AveF1measure[10:], 2)})
plot_avg_table(avg_results_df.iloc[:10])
# Plot average R/P curve
x_axis = np.linspace(0, 1, 11)
y_axis = compute_RP_yaxis(Precision=AvePrecision, Recall=AveRecall)
plt.plot(x_axis, y_axis, '-bo', color="blue", label="Average")
plt.xlim(0, 1)
plt.ylim(0, 1)
plt.xlabel('average Recall')
plt.ylabel('average Precision')
plt.title('Standard Average Recall/Precision Curves')
plt.legend()
plt.show()
LSI_y_axis_avg = y_axis
```

```
Results for top n docs returned for each query:
+-----
______
| Query |
                  Recall@1~10
Precision@1~10
                    F1measure@1~10
______
| Query1 | [0. 0.06 0.06 0.06 0.06 0.06 0.12 0.12 0.19 0.19] | [0. 0.5 0.33
0.24 0.23] |
| Query2 | [0. 0. 0. 0. 0. 0. 0. 0. 0.]
0. 0. 0. 0. 0. 0. 0. 0.]
                               [0. 0. 0. 0. 0. 0. 0. 0. 0.
0.]
   1
| Query3 | [0. 0. 0. 0. 0. 0.07 0.07 0.14 0.14] | [0. 0.
0. 0. 0.17 0.14 0.12 0.22 0.2 ] | [0. 0. 0. 0. 0. 0. 0.1 0.1 0.09
0.17 0.17] |
| Query4 | [0. 0. 0.07 0.14 0.21 0.29 0.36 0.43 0.5 0.5 ] | [0. 0. 0.33
0.5 0.6 0.67 0.71 0.75 0.78 0.7 ] | [0. 0. 0.12 0.22 0.32 0.4 0.48 0.55
0.61 0.58] |
         [0.2 0.2 0.2 0.4 0.4 0.4 0.4 0.4 0.6] | [1.
0.5 0.4 0.33 0.29 0.25 0.22 0.3 ] | [0.33 0.29 0.25 0.44 0.4 0.36 0.33 0.31
0.290.411
| Query6 | [0.08 0.08 0.17 0.25 0.25 0.25 0.25 0.25 0.25 0.25] | [1.
0.75 0.6 0.5 0.43 0.38 0.33 0.3 ] | [0.15 0.14 0.27 0.38 0.35 0.33 0.32 0.3
0.29 0.27] |
| Query7 | [0.07 0.14 0.21 0.29 0.36 0.43 0.5 0.57 0.64 0.71] |
1. 1. 1. 1. 1. 1. 1. 1. 1. | [0.13 0.25 0.35 0.44 0.53 0.6 0.67 0.73
0.78 0.831 L
| Query8 | [0.08 0.15 0.23 0.31 0.38 0.46 0.54 0.62 0.62 0.62] | [1. 1. 1.
1. 1. 1. 1. 0.89 0.8 ] | [0.14 0.27 0.38 0.47 0.56 0.63 0.7 0.76
0.73 0.7 ] |
______
```

40



+-	Query		Average	Recall@1~10	Average	Precision@1~10		Average	F1measure@1~10
+	1			0.44	 I	0.45			0.43
1	2	1		0.46	I	0.44	1		0.43
	3	I		0.48	I	0.43	I		0.44
   	4	I		0.48	I	0.4	I		0.43
	5	I		0.49	I	0.38	I		0.42
   	6	I		0.52	I	0.38	I		0.43
   	7	I		0.53	I	0.37	I		0.42
   	8	I		0.56	I	0.37	I		0.43
   	9	I		0.58	I	0.36	I		0.43
   	10	I		0.58	I	0.35	I		0.43
+-		-+-			+		-+-		



```
AllPrecision = list()
AllF1measure = list()
_y_axis_lsi_tf = list()
_y_axis_lsi_tfidf = list()
# Loop queries
for j, query in enumerate(querys):
 # Retrieval
 encoded_query = _preprocess_query(query, 'tfidf', vocab)
 transformed_query = trunc_SVD_model.transform(encoded_query)
 similarities = cosine_similarity(approx_Xtrain, transformed_query)
  # Rank the index
  indexes = np.argsort(similarities.flat)[::-1]
 doc_id = [data.iloc[indexes[i]]['ID'] for i in range(len(indexes))]
  # Mark the relevant index
 re mark = []
 for i in range(len(indexes)):
   if doc_id[i] in re_ID[j]:
     re_mark.append(1)
   else:
     re_mark.append(0)
  # Compute Recall, Precision, F1-measure
 Recall, Precision, F1measure = compute R P F1(re mark=re mark,
 →QuRe_ID=re_ID[j])
 print('\n' + 'Query%d: '%(j+1) + query)
 print("Recall@1~10: ", np.around(Recall[:10],2))
 print("Precision@1~10: ", np.around(Precision[:10],2))
 print("F1measure@1~10: ", np.around(F1measure[:10],2))
  # Save
 AllRecall.append(Recall)
 AllPrecision.append(Precision)
 AllF1measure.append(F1measure)
  # Plot R/P curve
 x_axis = [0.0, 0.1, 0.2, 0.3, 0.4, 0.5, 0.6, 0.7, 0.8, 0.9, 1.0]
  # Compute y-axis
 Recall = np.array(Recall)
 Precision = np.array(Precision)
 y_axis = compute_RP_yaxis(Precision=Precision, Recall=Recall)
  # Save y-axis for averaging later
```

```
_y_axis_lsi_tfidf.append(y_axis)
  # Plot R/P curve in subplot
  row = j // 4
  col = j \% 4
  axs[row, col].plot(x_axis, y_axis, '-bo', color="purple",_
 ⇔label="Query%d"%(j+1))
  axs[row, col].set_xlim(0, 1)
  axs[row, col].set_ylim(0, 1)
  axs[row, col].set_xlabel('Recall')
  axs[row, col].set_ylabel('Precision')
  axs[row, col].set_title('Query %d'%(j+1))
  axs[row, col].legend()
# Compute average Recall, average Precision, average F1-measure
AllRecall = np.array(AllRecall)
AllPrecision = np.array(AllPrecision)
AllF1measure = np.array(AllF1measure)
AveRecall = np.mean(AllRecall, axis=0)
AvePrecision = np.mean(AllPrecision, axis=0)
AveF1measure = np.mean(AllF1measure, axis=0)
# Plot average R/P curve
y_axis = compute RP_yaxis(Precision=AvePrecision, Recall=AveRecall)
for i in range(2):
 for j in range(4):
    axs[i, j].plot(x_axis, y_axis, '-bo', color="blue", label="Average")
    axs[i, j].set_xlim(0, 1)
    axs[i, j].set_ylim(0, 1)
    axs[i, j].set_xlabel('average Recall')
    axs[i, j].set_ylabel('average Precision')
    axs[i, j].set_title('Query Avg')
    axs[i, j] legend()
plt.show()
```

Query3: arrived promptly and happy with the seller

Recall@1~10: [0. 0. 0. 0. 0. 0.07 0.07 0.07 0.14 0.14]

Precision@1~10: [0. 0. 0. 0. 0.17 0.14 0.12 0.22 0.2]

Fimeasure@1~10: [0. 0. 0. 0. 0. 0.1 0.1 0.09 0.17 0.17]

Query4: wear it with casual wear

Recall@1~10: [0. 0. 0.07 0.14 0.21 0.29 0.36 0.43 0.5 0.5 ]

Precision@1~10: [0. 0. 0.33 0.5 0.6 0.67 0.71 0.75 0.78 0.7]

Fimeasure@1~10: [0. 0. 0.12 0.22 0.32 0.4 0.48 0.55 0.61 0.58]

Query5: i expected better quality. i will return this item

Recall@1~10: [0.2 0.2 0.2 0.4 0.4 0.4 0.4 0.4 0.6]

Precision@1~10: [1. 0.5 0.33 0.5 0.4 0.33 0.29 0.25 0.22 0.3 ]

Fimeasure@1~10: [0.33 0.29 0.25 0.44 0.4 0.36 0.33 0.31 0.29 0.4 ]

Query6: looks beautiful. The design is pretty. pefect and color is light

Recall@1~10: [0.08 0.08 0.17 0.25 0.25 0.25 0.25 0.25 0.25 0.25]

Precision@1~10: [1. 0.5 0.67 0.75 0.6 0.5 0.43 0.38 0.33 0.3 ]

F1measure@1~10: [0.15 0.14 0.27 0.38 0.35 0.33 0.32 0.3 0.29 0.27]

Query7: This ring looks nothing like the picture. the diamonds are small and not very noticeable

Recall@1~10: [0.07 0.14 0.21 0.29 0.36 0.43 0.5 0.57 0.64 0.71]

Precision@1~10: [1. 1. 1. 1. 1. 1. 1. 1. 1.]

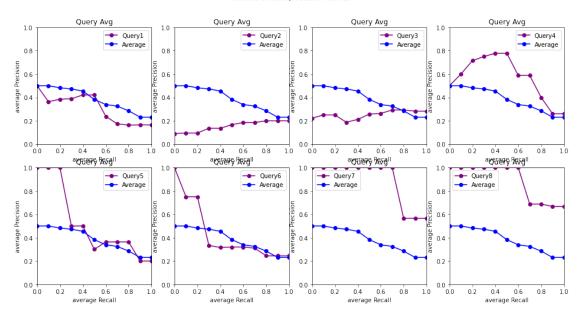
F1measure@1~10: [0.13 0.25 0.35 0.44 0.53 0.6 0.67 0.73 0.78 0.83]

Query8: braclet looked just like its picture and is nice quality sterling silver.

Recall@1~10: [0.08 0.15 0.23 0.31 0.38 0.46 0.54 0.62 0.62 0.62]

Precision@1~10: [1. 1. 1. 1. 1. 1. 1. 0.89 0.8]

F1measure@1~10: [0.14 0.27 0.38 0.47 0.56 0.63 0.7 0.76 0.73 0.7]



Tune Tf (Sublinear) and SVD dimension of 3

# 3 - Neural Information retrieval

Approach taken for Neural Information Retreival (NIR)

Overall, the cosine similarity approach to NIR is based on the ability of word embedding techniques to capture semantic relationships between words and the cosine similarity measure to compare query and document embeddings. This method has yielded promising results in improving the accuracy of traditional IR models.

Approach employed involved encoding the query and document text into vector representations, computing their cosine similarity, ranking the documents based on their scores, and evaluating the model's accuracy using metrics such as precision, recall, and F1 score using BERT.

# [14]: !pip install transformers

```
Looking in indexes: https://pypi.org/simple, https://us-python.pkg.dev/colab-
wheels/public/simple/
Requirement already satisfied: transformers in /usr/local/lib/python3.9/dist-
packages (4.27.1)
Requirement already satisfied: packaging>=20.0 in /usr/local/lib/python3.9/dist-
packages (from transformers) (23.0)
Requirement already satisfied: huggingface-hub<1.0,>=0.11.0 in
/usr/local/lib/python3.9/dist-packages (from transformers) (0.13.2)
Requirement already satisfied: regex!=2019.12.17 in
/usr/local/lib/python3.9/dist-packages (from transformers) (2022.10.31)
Requirement already satisfied: tokenizers!=0.11.3,<0.14,>=0.11.1 in
/usr/local/lib/python3.9/dist-packages (from transformers) (0.13.2)
Requirement already satisfied: requests in /usr/local/lib/python3.9/dist-
packages (from transformers) (2.27.1)
Requirement already satisfied: pyyaml>=5.1 in /usr/local/lib/python3.9/dist-
packages (from transformers) (6.0)
Requirement already satisfied: filelock in /usr/local/lib/python3.9/dist-
packages (from transformers) (3.10.0)
Requirement already satisfied: tqdm>=4.27 in /usr/local/lib/python3.9/dist-
packages (from transformers) (4.65.0)
Requirement already satisfied: numpy>=1.17 in /usr/local/lib/python3.9/dist-
packages (from transformers) (1.22.4)
Requirement already satisfied: typing-extensions>=3.7.4.3 in
/usr/local/lib/python3.9/dist-packages (from huggingface-
hub<1.0,>=0.11.0->transformers) (4.5.0)
Requirement already satisfied: certifi>=2017.4.17 in
/usr/local/lib/python3.9/dist-packages (from requests->transformers) (2022.12.7)
Requirement already satisfied: urllib3<1.27,>=1.21.1 in
/usr/local/lib/python3.9/dist-packages (from requests->transformers) (1.26.15)
Requirement already satisfied: idna<4,>=2.5 in /usr/local/lib/python3.9/dist-
packages (from requests->transformers) (3.4)
```

Requirement already satisfied: charset-normalizer~=2.0.0 in /usr/local/lib/python3.9/dist-packages (from requests->transformers) (2.0.12)

```
import numpy as np
import pandas as pd
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LogisticRegression
from sklearn.model_selection import GridSearchCV
from sklearn.model_selection import cross_val_score
import torch
import transformers as ppb
import warnings
warnings.filterwarnings('ignore')
```

Some weights of the model checkpoint at distilbert-base-uncased were not used when initializing DistilBertModel: ['vocab\_transform.bias', 'vocab\_transform.weight', 'vocab\_projector.bias', 'vocab\_layer\_norm.bias', 'vocab\_layer\_norm.weight', 'vocab\_projector.weight']

- This IS expected if you are initializing DistilBertModel from the checkpoint of a model trained on another task or with another architecture (e.g. initializing a BertForSequenceClassification model from a BertForPreTraining model).
- This IS NOT expected if you are initializing DistilBertModel from the checkpoint of a model that you expect to be exactly identical (initializing a BertForSequenceClassification model).

```
[17]: N = len(train_docs)

with torch.no_grad():
    # Tokenization
    tokenized = train_docs[0:N].apply((lambda x: tokenizer.encode(x,u)))

add_special_tokens=True)))

# padding
```

```
max_len = 0
          q = 0
          for i in tokenized.values:
              # BERT only accept maximum 512 values
              if len(i) > 512:
                  temp = tokenized.values[q]
                  tokenized.values[q] = temp[:512]
                  i = tokenized.values[q]
                  print('too much tokenized.values for BERT, only 512 are taken')
              # print(len(i))
              if len(i) > max_len:
                  max_len = len(i)
              q += 1
          padded = np.array([i + [0]*(max_len-len(i)) for i in tokenized.values])
          np.array(padded).shape
          # masking
          attention_mask = np.where(padded != 0, 1, 0)
          attention_mask.shape
          # run the model
          input_ids = torch.tensor(padded)
          attention_mask = torch.tensor(attention_mask)
          print(input_ids.shape)
          last_hidden_states = model(input_ids, attention_mask=attention_mask)
          train_features = last_hidden_states[0][:,0,:].numpy()
      print(len(train_features))
     torch.Size([200, 49])
     200
[18]: N2 = len(query_docs)
      with torch.no_grad():
          # Tokenization
          tokenized = query_docs[0:N2].apply((lambda x: tokenizer.encode(x,_
       →add_special_tokens=True)))
          # padding
          max_len = 0
```

```
q = 0
    for i in tokenized.values:
        # BERT only accept maximum 512 values
        if len(i) > 512:
            temp = tokenized.values[q]
            tokenized.values[q] = temp[:512]
            i = tokenized.values[q]
            print('too much tokenized.values for BERT, only 512 are taken')
        # print(len(i))
        if len(i) > max_len:
            max_len = len(i)
        q += 1
    padded = np.array([i + [0]*(max_len-len(i)) for i in tokenized.values])
    np.array(padded).shape
    # masking
    attention_mask = np.where(padded != 0, 1, 0)
    attention_mask.shape
    # run the model
    input_ids = torch.tensor(padded)
    attention_mask = torch.tensor(attention_mask)
    print(input_ids.shape)
    last_hidden_states = model(input_ids, attention_mask=attention_mask)
    query_features = last_hidden_states[0][:,0,:].numpy()
print(len(query_features))
torch.Size([8, 9])
```

torch.Size([8, 9])

## 3.1 3a - Evaluate approach 1

```
[19]: # Top_n_rankings = 3
# # Compute relevance scores and rank documents
# bert_similarity_scores = cosine_similarity(query_features, train_features)
# ranking = bert_similarity_scores.argsort()[:, ::-1]
# # indexes = np.argsort(bert_similarity_scores.flat)[-Top_n_rankings:]
# # print(ranking)
# # print("ESSS")
# # print(indexes)
# # print("ESSS")
# # print(ranking[0, :1][0])
```

```
# doc_list = list()
# AllRecall = []
# AllPrecision = []
# AllF1measure = [7
# # loop queries
# j = 0
# for key, value in enumerate(ranking):
   query ids = ranking[key, :Top n rankings]
   indexes = np.argsort(query_ids)
   d_id = [i \text{ for } i \text{ in } query_ids]
#
   ndoc_id = [data.iloc[k]['ID'] for k in query_ids]
   ndoc_text = [data.iloc[k]['Reviews'] for k in query_ids]
#
 # print(query_ids)
# print(d_id)
#
  print(indexes)
#
   print('**')
# print(ndoc_id)
#
   # print(ndoc_text)
  doc_list.append(ndoc_id)
#
# print(' '*100)
   print(f'Query ids {key + 1}: {querys[key]}')
  # print(f'Query {key + 1}: {querys[key]}')
#
  print('='*100)
# print(f"Retrieved documents: {str(ndoc id)}")
   # BERT_similarity_scores = ', '.join([str(round(score, 3)) for score in_
\rightarrowquery_ids])
  BERT_similarity_score = ', '.join([str(round(score, 3)) for score in_
 ⇔bert similarity scores.
#
                                  flat[d_id]])
   print(f"\nSimilarities scores: {BERT_similarity_score}")
#
   print('='*100)
   for i in range(Top n reviews, 0, -1):
    print(f"{i}th Ranked result:")
#
#
     print("Doc ID: " + str(indexes[-i]))
#
      # print("ID"+ str(data.iloc[indexes[i]]))
#
     # print(reviews[indexes[-i]])
#
    print(docs[indexes[-i]])
     print("Similarities: " + str(similarities.flat[indexes[-i]]))
#
     print(' \mid n')
   for q in query_ranks:
#
    print(q)
     print(data.iloc[q]['ID'])
#
#
   print(data.iloc[ranking[i, :Top_n_rankings][i]])
   # Mark the relevant index
```

```
# bert_re_mark = []
# for i in range(len(query_ranks)):
  print(ndoc_id[i])
  print(re_ID[i])
# if (ndoc_id[i]) in re_ID[i]:
    bert_re_mark.append(1)
#
#
 else:
#
    bert_re_mark.append(0)
  # print(re mark)
# # compute Recall, Precision, F1-measure
# Recall, Precision, F1measure = compute_R_P_F1(re_mark=bert_re_mark,_
→QuRe ID=re ID[j])
# print('\n' + 'Query%d: '%(j+1) + querys[i])
# # for i in range(10):
# # print("Top " + str(i+1) + ' result: ID%d '%(indexes[i]+1),__
\rightarrow ArRe_train_lines[indexes[i]])
# Recall = np.array(Recall)
# Precision = np.array(Precision)
# F1measure = np.array(F1measure)
# # print(re_mark)
# print("Recall@1~10: ", np.around(Recall[:10],2))
# print("Precision@1~10: ", np.around(Precision[:10],2))
# print("F1measure@1~10: ", np.around(F1measure[:10],2))
# # save
# AllRecall.append(Recall)
# AllPrecision.append(Precision)
# AllF1measure.append(F1measure)
# # plot R/P curve
\# x_axis = [0.0, 0.1, 0.2, 0.3, 0.4, 0.5, 0.6, 0.7, 0.8, 0.9, 1.0]
# y axis = compute RP yaxis(Precision=Precision, Recall=Recall)
# plt.plot(x_axis, y_axis, '-bo', color="purple", label="Query%d"%(j+1))
# plt.xlim(0, 1)
# plt.ylim(0, 1)
# plt.xlabel('Recall')
# plt.ylabel('Precision')
# plt.title('Standard Recall/Precision Curves')
# plt.legend()
# plt.show()
# j += 1
# # compute average Recall, average Precision, average F1-measure
# AllRecall = np.array(AllRecall)
```

```
# AllPrecision = np.array(AllPrecision)
# AllF1measure = np.array(AllF1measure)
# AveRecall = (AllRecall[:,0] + AllRecall[:,1] + AllRecall[:,2] + AllRecall[:
\Rightarrow,3] + AllRecall[:,4] + AllRecall[:,5] + AllRecall[:,6] + AllRecall[:,7])/8
\# AvePrecision = (AllPrecision[0] + AllPrecision[1]+AllPrecision[2] +
 AllPrecision[3]+AllPrecision[4] + AllPrecision[5] + AllPrecision[6] +
 \hookrightarrow AllPrecision[7])/8
\# AveF1measure = (AllF1measure[0] + AllF1measure[1]+AllF1measure[2] +
 AllF1measure[3]+AllF1measure[4] + AllF1measure[5] + AllF1measure[6] +
\rightarrow AllF1measure[7])/8
# print("\nAverage Recall, average Precision, average F1-measure: ")
# print("average Recall@1~10: ", np.around(AveRecall[:10],2))
# print("average Precision@1~10: ", np.around(AvePrecision[:10],2))
# print("average F1measure@1~10: ", np.around(AveF1measure[:10],2))
# # plot average R/P curve
\# x_axis = [0.0, 0.1, 0.2, 0.3, 0.4, 0.5, 0.6, 0.7, 0.8, 0.9, 1.0]
# y_axis = compute_RP_yaxis(Precision=AvePrecision, Recall=AveRecall)
# plt.plot(x_axis, y_axis, '-bo', color="blue", label="Average")
# plt.xlim(0, 1)
# plt.ylim(0, 1)
# plt.xlabel('average Recall')
# plt.ylabel('average Precision')
# plt.title('Standard Average Recall/Precision Curves')
# plt.legend()
# plt.show()
```

## 3.2 Aproach 3

```
[20]: # Top_n_rankings = 3

# # Compute relevance scores and rank documents
# bert_similarity_scores = cosine_similarity(query_features, train_features)
# ranking = bert_similarity_scores.argsort()[:, ::-1]

# doc_list = []
# AllRecall = []
# AllPrecision = []
# AllFimeasure = []

# # Loop through queries
# for key, value in enumerate(ranking):
# query_ids = ranking[key, :Top_n_rankings]
# indexes = np.argsort(query_ids)[::-1]
```

```
#
      d_id = [i \text{ for } i \text{ in } query_ids]
#
      ndoc_id = [data.iloc[k]['ID'] for k in query_ids]
#
      ndoc_text = [data.iloc[k]['Reviews'] for k in query_ids]
#
      doc_list.append(ndoc_id)
      print('_'*100)
#
#
      print(f'Query ids {key + 1}: {querys[key]}')
#
      print('='*100)
      print(f"Retrieved documents: {str(ndoc id)}")
      # Compute cosine similarity for each retrieved document and print results
#
      for i in range(Top_n_rankings):
#
          print(f"{i+1}th ranked result:")
#
          doc_index = indexes[i]
#
          doc id = ndoc id[doc index]
          doc_text = ndoc_text[doc_index]
#
          similarity_score = bert_similarity_scores[key, doc_index]
#
          print(f"Doc ID: {doc_id}")
          print(f"Doc Text: {doc_text}")
#
          print(f"Similarity Score: {similarity_score}\n")
          # Mark the relevant index
#
#
      re\ mark = []
      for i in range(len(indexes)):
#
#
        if (doc_list[i]) in re_ID[j]:
          re_mark.append(1)
        else:
          re mark.append(0)
#
      # print(re_mark)
#
      # compute Recall, Precision, F1-measure
      Recall, Precision, F1measure = compute_R_P_F1(re_mark=re_mark,_
 →QuRe_ID=re_ID[j])
      print('\n' + 'Query\%d: '\%(j+1) + query)
#
      # for i in range(10):
        print("Top " + str(i+1) + ' result: ID%d '%(indexes[i]+1),
 → ArRe_train_lines[indexes[i]])
      Recall = np.array(Recall)
#
      Precision = np.array(Precision)
#
      F1measure = np.array(F1measure)
#
      # print(re_mark)
      print("Recall@1~10: ", np.around(Recall[:10],2))
#
      print("Precision@1~10: ", np.around(Precision[:10],2))
      print("F1measure@1~10: ", np.around(F1measure[:10],2))
#
      # save
```

```
AllRecall.append(Recall)
#
      AllPrecision.append(Precision)
      AllF1measure.append(F1measure)
#
#
      # plot R/P curve
#
      x_axis = [0.0, 0.1, 0.2, 0.3, 0.4, 0.5, 0.6, 0.7, 0.8, 0.9, 1.0]
      y axis = compute RP yaxis(Precision=Precision, Recall=Recall)
#
#
      plt.plot(x_axis, y_axis, '-bo', color="purple", label="Query%d"%(j+1))
#
     plt.xlim(0, 1)
#
     plt.ylim(0, 1)
#
     plt.xlabel('Recall')
     plt.ylabel('Precision')
#
     plt.title('Standard Recall/Precision Curves')
#
     plt.legend()
#
     plt.show()
#
      j += 1
      # compute average Recall, average Precision, average F1-measure
     AllRecall = np.array(AllRecall)
     AllPrecision = np.array(AllPrecision)
#
     AllF1measure = np.array(AllF1measure)
      AveRecall = (AllRecall[0] + AllRecall[1] + AllRecall[2] + AllRecall[3] +
 AllRecall[4] + AllRecall[5] + AllRecall[6] + AllRecall[7])/8
      AvePrecision = (AllPrecision[0] + AllPrecision[1] + AllPrecision[2] + L
 AllPrecision[3]+AllPrecision[4] + AllPrecision[5] + AllPrecision[6] +
 →AllPrecision[7])/8
      AveF1measure = (AllF1measure[0] + AllF1measure[1] + AllF1measure[2] + ___
 \rightarrow AllF1measure[3]+AllF1measure[4] + AllF1measure[5] + AllF1measure[6] +
 →AllF1measure[7])/8
      print("\nAverage Recall, average Precision, average F1-measure: ")
      print("average Recall@1~10: ", np.around(AveRecall[:10],2))
     print("average Precision@1~10: ", np.around(AvePrecision[:10],2))
#
     print("average F1measure@1~10: ", np.around(AveF1measure[:10],2))
#
      # plot average R/P curve
#
      x_axis = [0.0, 0.1, 0.2, 0.3, 0.4, 0.5, 0.6, 0.7, 0.8, 0.9, 1.0]
#
      y_axis = compute_RP_yaxis(Precision=AvePrecision, Recall=AveRecall)
      plt.plot(x_axis, y_axis, '-bo', color="blue", label="Average")
#
     plt.xlim(0, 1)
#
     plt.ylim(0, 1)
     plt.xlabel('average Recall')
#
     plt.ylabel('average Precision')
#
     plt.title('Standard Average Recall/Precision Curves')
#
     plt.legend()
      plt.show()
```

# 3.3 3a - Approach 4

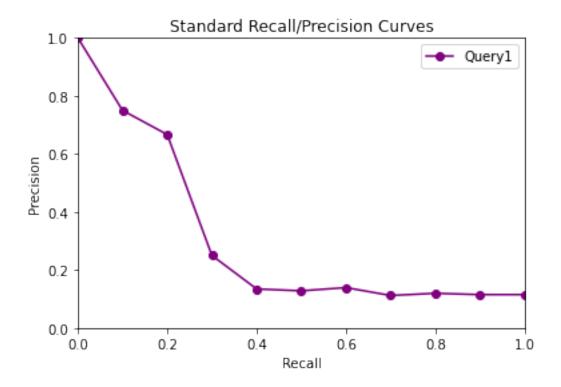
```
[21]: Top n rankings = 10
      BERT_AllRecall = list()
      BERT AllPrecision = list()
      BERT AllF1measure = list()
      _y_axis = list()
      _avg_y_axis = list()
      j = 0
      for key,value in enumerate(querys):
        Q_features = query_features[key,:]
        Q_features = Q_features.reshape(1,-1)
        BERT_similarity_scores = cosine similarity(train_features,Q_features)
        # ###
        BERT_idx = np.argsort(BERT_similarity_scores.flat)[::-1]
        doc_id = [data.iloc[BERT_idx[i]]["ID"] for i in range(len(BERT_idx))]
        # #####
        BERT_doc_idx = []
        for i in range(len(BERT idx)):
          BERT_doc_idx.append(doc_id[i])
        # ###
        BERT re mark = []
        for i in range(len(BERT idx)):
          if (BERT_doc_idx[i]) in re_ID[j]:
            BERT_re_mark.append(1)
          else:
            BERT_re_mark.append(0)
        # compute Recall, Precision, F1-measure
        BERT_Recall, BERT_Precision, BERT_F1measure =
       →compute_R_P_F1(re_mark=BERT_re_mark, QuRe_ID=re_ID[j])
        print('\n' + 'Query%d: '%(j+1) + query)
        for x in range(Top_n_rankings):
          print("Top " + str(x+1) + ' result: ID%d '%(BERT_doc_idx[x]),__
       →reviews[BERT_idx[x]])
        BERT_Recall = np.array(BERT_Recall)
        BERT_Precision = np.array(BERT_Precision)
        BERT_F1measure = np.array(BERT_F1measure)
        # print(re mark)
        print("Recall@1~10: ", np.around(BERT_Recall[:10],2))
        print("Precision@1~10: ", np.around(BERT_Precision[:10],2))
        print("F1measure@1~10: ", np.around(BERT_F1measure[:10],2))
        # save
        BERT_AllRecall.append(BERT_Recall)
```

```
BERT_AllPrecision.append(BERT_Precision)
 BERT_AllF1measure.append(BERT_F1measure)
  # plot R/P curve
 x_{axis} = [0.0, 0.1, 0.2, 0.3, 0.4, 0.5, 0.6, 0.7, 0.8, 0.9, 1.0]
 y_axis = compute_RP_yaxis(Precision=BERT_Precision, Recall=BERT_Recall)
 _y_axis.append(y_axis)
 plt.plot(x_axis, y_axis, '-bo', color="purple", label="Query%d"%(j+1))
 plt.xlim(0, 1)
 plt.ylim(0, 1)
 plt.xlabel('Recall')
 plt.ylabel('Precision')
 plt.title('Standard Recall/Precision Curves')
 plt.legend()
 plt.show()
 j += 1
# compute average Recall, average Precision, average F1-measure
BERT_AllRecall = np.array(BERT_AllRecall)
BERT_AllPrecision = np.array(BERT_AllPrecision)
BERT AllF1measure = np.array(BERT AllF1measure)
#calculate the average metrices for 8 queries
BERT AveRecall = (BERT AllRecall[0] + BERT AllRecall[1] + BERT AllRecall[2] +
→BERT_AllRecall[3] + BERT_AllRecall[4] + BERT_AllRecall[5] +
→BERT_AllRecall[6] + BERT_AllRecall[7])/8
BERT_AvePrecision = (BERT_AllPrecision[0] + BERT_AllPrecision[1] +
 →BERT_AllPrecision[2] + BERT_AllPrecision[3] + BERT_AllPrecision[4] +
 →BERT_AllPrecision[5] + BERT_AllPrecision[6] + BERT_AllPrecision[7])/8
BERT_AveF1measure = (BERT_AllF1measure[0] + BERT_AllF1measure[1] +
 ⇒BERT_AllF1measure[2] + BERT_AllF1measure[3] + BERT_AllF1measure[4] +
 →BERT_AllF1measure[5] + BERT_AllF1measure[6] + BERT_AllF1measure[7])/8
print("\nAverage Recall, average Precision, average F1-measure: ")
print("average Recall01~10: ", np.around(BERT_AveRecall[:10],2))
print("average Precision@1~10: ", np.around(BERT_AvePrecision[:10],2))
print("average F1measure@1~10: ", np.around(BERT_AveF1measure[:10],2))
# plot average R/P curve
x_{axis} = [0.0, 0.1, 0.2, 0.3, 0.4, 0.5, 0.6, 0.7, 0.8, 0.9, 1.0]
y_axis = compute_RP_yaxis(Precision=BERT_AvePrecision, Recall=BERT_AveRecall)
plt.plot(x_axis, y_axis, '-bo', color="blue", label="Average")
plt.xlim(0, 1)
plt.ylim(0, 1)
plt.xlabel('average Recall')
plt.ylabel('average Precision')
plt.title('Standard Average Recall/Precision Curves')
```

```
plt.legend()
plt.show()

BERT_y_axis_avg = y_axis
```

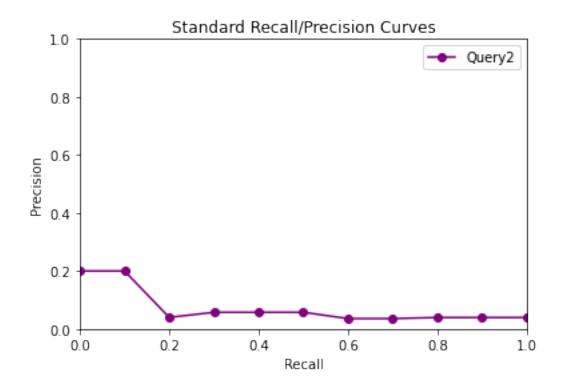
Query1: braclet looked just like its picture and is nice quality sterling silver. Top 1 result: ID41876 bought friends birthday loved gift ring Top 2 result: ID58595 absolutely got beautiful engagement love durable ring Top 3 result: ID48779 got rings thing ring love gift Top 4 result: ID58481 cheap great loves high gift quality wife ring Top 5 result: ID3865 dainty pretty looking sparkle Top 6 result: ID26246 happy ring received loves gift birthday Top 7 result: ID6522 love suggest jewelry collection every ring Top 8 result: ID48216 got birthday imagine love adoring ring woman Top 9 result: ID45203 got birthday imagine love adoring ring woman Top 10 result: ID25299 bracelet true perfect nice quality necklace Recall@1~10: [0.06 0.06 0.12 0.19 0.19 0.25 0.25 0.25 0.25 0.25] 0.5 0.67 0.75 0.6 0.67 0.57 0.5 0.44 0.4 ] Precision@1~10: [1. Fimeasure@1~10: [0.12 0.11 0.21 0.3 0.29 0.36 0.35 0.33 0.32 0.31]



Query2: braclet looked just like its picture and is nice quality sterling

#### silver.

Top 1 result: ID9050 enough metal pretty easily ring Top 2 result: ID41876 bought friends birthday loved gift ring Top 3 result: ID19944 pleased use purchase shipping Top 4 result: ID2134 wearing Top 5 result: ID25299 bracelet true perfect nice quality necklace Top 6 result: ID3865 dainty pretty looking sparkle Top 7 result: ID58595 absolutely got beautiful engagement love durable ring Top 8 result: ID22058 promptly item happy great came quality recommend Top 9 result: ID58481 cheap great loves high gift quality wife ring Top 10 result: ID48779 got rings thing ring love gift Recall@1~10: [0. 0. 0. 0. 0.17 0.17 0.17 0.17 0.17 0.17] 0.2 0.17 0.14 0.12 0.11 0.1 ] Precision@1~10: [0. 0. 0. 0. F1measure@1~10: [0. 0. 0. 0.18 0.17 0.15 0.14 0.13 0.12] 0.



Query3: braclet looked just like its picture and is nice quality sterling silver.

Top 1 result: ID22058 promptly item happy great came quality recommend

Top 2 result: ID37896 around ring comfortable wish great way

Top 3 result: ID19944 pleased use purchase shipping Top 4 result: ID3865 dainty pretty looking sparkle

Top 5 result:  ${\tt ID42026}$  like small rings clearly fast ring product amazon guess

came

Top 6 result: ID17607 expecting seemed returned clearly product quality item

description poor

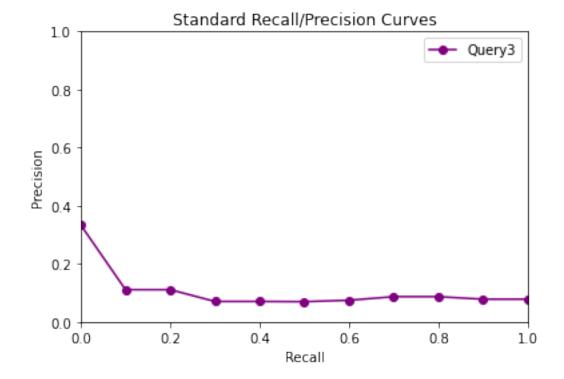
Top 7 result: ID30926 looks manner recommend timely ring would garnet

Top 8 result: ID11247 wanted love price always

Top 9 result: ID209 nothing like looks small diamonds picture ring sending back

Top 10 result: ID47345 nothing like looked diamonds picture bit product little

nt



Query4: braclet looked just like its picture and is nice quality sterling silver.

Top 1 result: ID53660 something nice casual want comfortable wear

Top 2 result: ID19852 good wear everyday

Top 3 result: ID30640 enough detail nice wear colors suit perfect

Top 4 result: ID2134 wearing

Top 5 result: ID44135 index great fits comfortable awesome finger ring wear Top 6 result: ID50640 index great fits comfortable awesome finger ring wear

Top 7 result: ID11087 favorite wear mine wanted

Top 8 result: ID37486 work wear pendant going casual nt

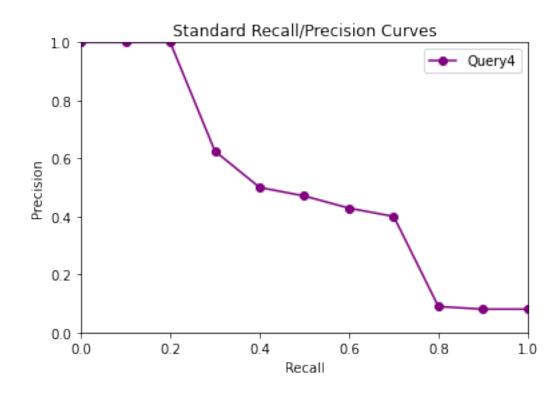
Top 9 result: ID3865 dainty pretty looking sparkle

Top 10 result: ID52663 please ring wear comfortable quite see

Recall@1~10: [0.07 0.14 0.21 0.29 0.29 0.29 0.29 0.36 0.36 0.36]

Precision@1~10: [1. 1. 1. 0.8 0.67 0.57 0.62 0.56 0.5]

F1measure@1~10: [0.13 0.25 0.35 0.44 0.42 0.4 0.38 0.45 0.43 0.42]



Query5: braclet looked just like its picture and is nice quality sterling silver.

Top 1 result: ID1816 would look item quality recommend

Top 2 result: ID13373 pictured quality seller item poor

Top 3 result: ID17607 expecting seemed returned clearly product quality item

description poor

Top 4 result: ID45548 item attractive high quality small

Top 5 result: ID17944 expected nice product order item came

Top 6 result: ID22058 promptly item happy great came quality recommend

Top 7 result: ID19852 good wear everyday

Top 8 result: ID19944 pleased use purchase shipping

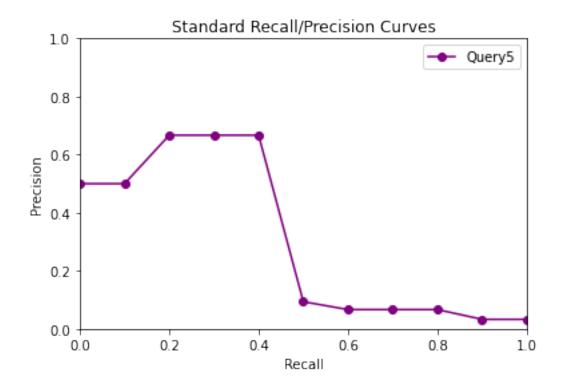
Top 9 result: ID22946 would better pinky little finger small ring

Top 10 result: ID42026 like small rings clearly fast ring product amazon guess came

Recall@1~10: [0. 0.2 0.4 0.4 0.4 0.4 0.4 0.4 0.4 0.4]

Precision@1~10: [0. 0.5 0.67 0.5 0.4 0.33 0.29 0.25 0.22 0.2]

F1measure@1~10: [0. 0.29 0.5 0.44 0.4 0.36 0.33 0.31 0.29 0.27]



Query6: braclet looked just like its picture and is nice quality sterling silver.

Top 1 result: ID52375 bought looks present nice pretty color

Top 2 result: ID39932 absolutely looks heart price amazing pendant dainty

colors beautiful

Top 3 result: ID44490 like look described small good light nice picture quality

size

Top 4 result: ID37794 like look price earrings polished good light picture quality comfortable silver stones

Top 5 result: ID50197 look smooth beautiful

Top 6 result: ID735 like looks really nice picture charm enamel nicely size

perfect either side solid silver

Top 7 result: ID36165 like look person small diamonds smaller alot ring

pictures size little make disappointed

Top 8 result: ID42077 buy pink expecting saw picture pretty first thought ring still color barely design disappointed

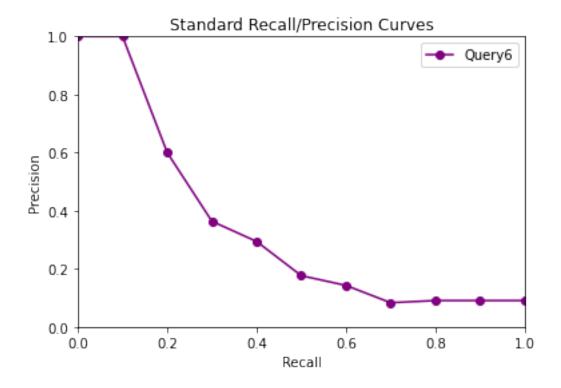
Top 9 result: ID642 like silver picture nice quality sterling looked

Top 10 result: ID943 like look looks online real picture looking ring life man

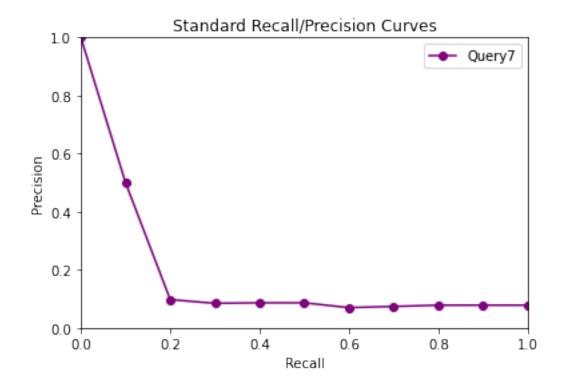
Recall@1~10: [0.08 0.17 0.17 0.17 0.25 0.25 0.25 0.25 0.25 0.25]

Precision@1~10: [1. 1. 0.67 0.5 0.6 0.5 0.43 0.38 0.33 0.3]

Fimeasure@1~10: [0.15 0.29 0.27 0.25 0.35 0.33 0.32 0.3 0.29 0.27]



Query7: braclet looked just like its picture and is nice quality sterling silver. Top 1 result: ID209 nothing like looks small diamonds picture ring sending back Top 2 result: ID3865 dainty pretty looking sparkle Top 3 result: ID3494 like looks nice picture Top 4 result: ID47345 nothing like looked diamonds picture bit product little Top 5 result: ID10642 clear like looked purple picture Top 6 result: ID9050 enough metal pretty easily ring Top 7 result: ID41876 bought friends birthday loved gift ring Top 8 result: ID48779 got rings thing ring love gift Top 9 result: ID58595 absolutely got beautiful engagement love durable ring Top 10 result: ID50197 look smooth beautiful Recall@1~10: [0.07 0.07 0.07 0.14 0.14 0.14 0.14 0.14 0.14] Precision@1~10: [1. 0.5 0.33 0.5 0.4 0.33 0.29 0.25 0.22 0.2 ] Fimeasure@1~10: [0.13 0.12 0.12 0.22 0.21 0.2 0.19 0.18 0.17 0.17]



Query8: braclet looked just like its picture and is nice quality sterling silver.

Top 1 result: ID642 like silver picture nice quality sterling looked

Top 2 result: ID45518 like expected seemed looked necklace much smaller picture quality silver

Top 3 result: ID37794 like look price earrings polished good light picture quality comfortable silver stones

Top 4 result: ID57123 worth bracelet appearance close definitely quality even disappointed

Top 5 result: ID44490 like look described small good light nice picture quality size

Top 6 result: ID735 like looks really nice picture charm enamel nicely size perfect either side solid silver

Top 7 result: ID44489 like look got nice picture far christmas gift

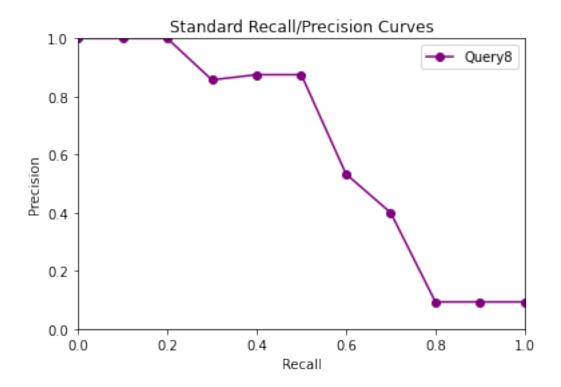
Top 8 result: ID10642 clear like looked purple picture

Top 9 result: ID12358 like look seen price high know quite beautiful

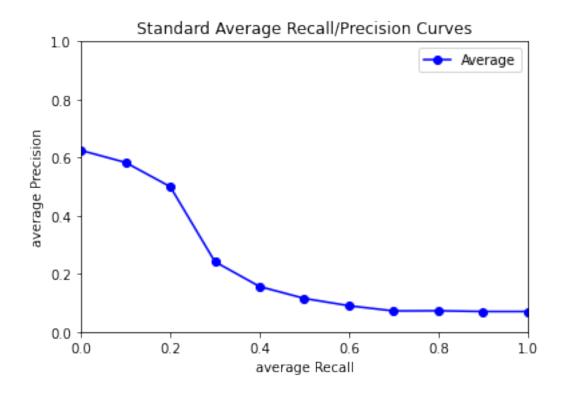
Top 10 result: ID52375 bought looks present nice pretty color Recall@1~10: [0.08 0.15 0.23 0.23 0.31 0.38 0.46 0.54 0.54 0.54]

Precision@1~10: [1. 1. 0.75 0.8 0.83 0.86 0.88 0.78 0.7]

F1measure@1~10: [0.14 0.27 0.38 0.35 0.44 0.53 0.6 0.67 0.64 0.61]



Average Recall, average Precision, average F1-measure: average Recall@1~10: [0.05 0.1 0.16 0.19 0.23 0.24 0.25 0.27 0.27 0.27] average Precision@1~10: [0.62 0.56 0.58 0.53 0.5 0.46 0.41 0.39 0.35 0.31] average F1measure@1~10: [0.09 0.17 0.24 0.27 0.3 0.31 0.3 0.31 0.29 0.28]



## 3a Comparisim

```
[22]: # for key, value in enumerate(querys):
        # plot R/P curves for models being compared (LSI and Neural Information_
       →Retrival (NIR))
        # print('\n' + 'Query%d: '%(index+1) + query)
        \# x_axis = [0.0, 0.1, 0.2, 0.3, 0.4, 0.5, 0.6, 0.7, 0.8, 0.9, 1.0]
        # plot_LSI = _y_axis_lsi_tfidf[index]
        \# plot_NIR = \_y\_axis[index]
        # plt.plot(x axis, plot LSI, '-bo', color="green", label="Query%d withu
       \hookrightarrowLSI"%(index+1))
        # plt.plot(x_axis, plot_NIR, '-bo', color="red", label="Query%d with_
       \hookrightarrow NRI''\%(index+1))
        # plt.xlim(0, 1)
        # plt.ylim(0, 1)
        # plt.xlabel('Recall')
        # plt.ylabel('Precision')
        # plt.title('Standard Recall/Precision - Compare LSI and Neural Approach')
        # plt.legend()
        # plt.show()
      # plot R/P average curves for models being compared (LSI and Neural Information
       ⇔Retrival (NIR))
```

```
[23]: from prettytable import PrettyTable
      fig, axs = plt.subplots(nrows=2, ncols=4, figsize=(16, 8))
      table = PrettyTable()
      table.field names = ["Query", "LSI Precision", "LSI Recall", "NIR Precision", "
       →"NIR Recall"]
      for key, (query, index) in enumerate(zip(querys, range(len(querys)))):
          # plot R/P curves for both methods(NIR and LSI)
         print('\n' + 'Query%d: '%(index+1) + query)
         x_axis = [0.0, 0.1, 0.2, 0.3, 0.4, 0.5, 0.6, 0.7, 0.8, 0.9, 1.0]
         plot LSI = y axis lsi tfidf[index]
         plot_NIR = _y_axis[index]
         row = key // 4
         col = key \% 4
         ax = axs[row, col]
         ax.plot(x axis, plot LSI, '-bo', color="green", label="Query%d withu
       ax.plot(x_axis, plot_NIR, '-bo', color="red", label="Query%d withu

SIR"%(index+1))
         ax.set_xlim(0, 1)
         ax.set_ylim(0, 1)
         ax.set_xlabel('Recall')
         ax.set_ylabel('Precision')
         ax.set_title('Query%d - Compare LSI and Neural Approach'%(index+1))
         ax.legend()
          # calculate R/P values
         LSI_precision = _y_axis_lsi_tfidf[index][5]
         LSI_recall = x_axis[5]
         NIR_precision = _y_axis[index][5]
         NIR_recall = x_axis[5]
```

```
# add R/P values to the table
table.add_row([query, round(LSI_precision, 2), round(LSI_recall, 2),
round(NIR_precision, 2), round(NIR_recall, 2)])

plt.tight_layout()
plt.show()
print(table)
```

Query1: The ring is a great gift. My friend loves it

Query2: horrible bad quality bracelet

Query3: arrived promptly and happy with the seller

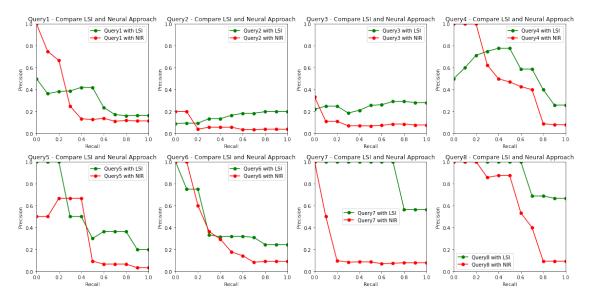
Query4: wear it with casual wear

Query5: i expected better quality. i will return this item

Query6: looks beautiful. The design is pretty. pefect and color is light

Query7: This ring looks nothing like the picture. the diamonds are small and not very noticeable

Query8: braclet looked just like its picture and is nice quality sterling silver.



```
Query
| LSI Precision | LSI Recall | NIR Precision | NIR Recall |
     The ring is a great gift. My friend loves it
      0.42
                  0.5
                               0.13
                                           0.5
                          horrible bad quality bracelet
     0.17
                  0.5
                               0.06
                         0.5
                     arrived promptly and happy with the seller
     0.26
                               0.07
                                           0.5
                  0.5
                         wear it with casual wear
     0.78
                               0.47
                  0.5
                                           0.5
                  i expected better quality. i will return this item
      0.3
                               0.09
                        0.5
            looks beautiful. The design is pretty. pefect and color is light
      0.32
                  0.5
                               0.18
                                      0.5
| This ring looks nothing like the picture. the diamonds are small and not very
noticeable |
              1.0
                      - 1
                           0.5
                                  0.09
                                                0.5
       braclet looked just like its picture and is nice quality sterling
                                0.5
                                             0.88
                                                         0.5
silver.
                    1.0
```

#### 3.4 3b - An Interactive interface for users to type in their own query

```
[24]: def build_query_embedding(query, n):
        query_doc = pd.Series(query)
        with torch.no_grad():
            # Tokenization
            tokenized = query_doc[0:n].apply((lambda x: tokenizer.encode(x,_
       →add_special_tokens=True)))
            # padding
            max_len = 0
            q = 0
            for i in tokenized.values:
                # BERT only accept maximum 512 values
                if len(i) > 512:
                    temp = tokenized.values[q]
                    tokenized.values[q] = temp[:512]
                    i = tokenized.values[q]
                    print('too much tokenized.values for BERT, only 512 are taken')
                # print(len(i))
```

```
[25]: from prettytable import PrettyTable, ALL
      def search(query, n_results=5):
        # Get the query embedding using the BERT-based model
        embedding = build_query_embedding(query, n_results)
        # Calculate the cosine similarity between the query embedding and the
       → document embeddings
        similarity = cosine_similarity(train_features, embedding)
        # Get the indexes of the top n_results most similar documents sorted by \sqcup
       ⇔similarity score
        indexes = np.argsort(similarity, axis=None)[::-1][:n_results]
        # Get the document IDs, texts, and similarity scores of the top n results \Box
       →most similar documents
        d_id = [i for i in indexes]
        ndoc_id = [data.iloc[k]['ID'] for k in indexes]
        ndoc_text = [data.iloc[k]['Reviews'] for k in indexes]
        similarity_scores = [np.around(similarity[k], 4) for k in indexes]
        # Return the query IDs, document IDs, document texts, and similarity scores
        return d_id, ndoc_id, ndoc_text, similarity_scores
      def print_search_results(d_id, ndoc_id, ndoc_text, similarity_scores):
        # Create a PrettyTable object to format the search results
        results = PrettyTable()
        # Set the field names and formatting options for the table
```

```
results.field_names = ["Rank", "Doc ID", "Score", "Text"]
      results.hrules = ALL
      results.vrules = ALL
      results.align["Rank"] = "c"
      results.align["Doc ID"] = "1"
      results.align["Similarity Score"] = "c"
      results.align["Text"] = "1"
      results.float_format = ".4"
      # Add the query as the first row of the table
      results.add_row(["Query", "", "", query])
      # Add the top n_results most similar documents to the table
      for i in range(n_results):
        results.add_row([i+1, ndoc_id[i], similarity_scores[i], ndoc_text[i]])
      # Print the formatted table
      print(results)
[26]: n_results = 10 #@param {type: "slider", min:1, max:10, step:1}
     # Get the query and rank from the user using input forms
[27]: query = input("Enter your query:")
     # n results = int(input("Enter the number of results you want to retrieve:"))
     _id, ndoc_id, doc_text, similarity = search(query, n_results)
     print_search_results(_id, doc_id, doc_text, similarity)
    Enter your query: Pretty necklace. Perfet gift
    | Rank | Doc ID | Score | Text
    | Query |
                           | Pretty necklace. Perfet gift
    +-----
    ----+
       1 | 642
                 | [0.9757] | the bracelet was not a true 9 the necklace
    perfect the bracelet nice quality just not true to length
```

+   2   45518   [0.9727]   i got this ring as a gift from my boyfriend and i love it. the only thing is that if the rings are not position correctly it pinches the skin.
+   3   37794   [0.9719]   I absolutely love this ring! I got this as my
engagement ring Feb 09 This ring is beautiful and durable.
+   4   57123   [0.9709]   I bought this as a gift for a friends birthday and she loved it. It's a beautifull ring.
+
+
+   6   735   [0.9709]   I got this ring for my birthday and I love it, I cannot imagine a woman not adoring this ring.
+   7   44489   [0.9707]   my wife loves the ring, it was a great gift. extremelly cheap and high quality.
+   8   10642   [0.9706]   I love the ring and suggest every girl should have this ring in their jewelry collection.
+
+   9   12358   [0.9696]   This was a birthday gift for my 16 YO niece. She loves the ring and was very happy to have received it.

```
[28]: queries = ['The ring is a great gift. My friend loves it',
                'horrible bad quality bracelet',
                'arrived promptly and happy with the seller',
                'wear it with casual wear',
                'i expected better quality. i will return this item',
                'looks beautiful. The design is pretty. pefect and color is light',
                'This ring looks nothing like the picture. the diamonds are small and \sqcup
       ⇔not very noticeable',
                'braclet looked just like its picture and is nice quality sterling⊔
       ⇔silver.'
      corpus_list = list()
      for index, query in enumerate(queries):
        query_id, query_doc_id, query_doc_text, query_similarity = search(query,_
       →n results)
        print('\n' + f"QUERY {index+1} - {query}")
        print_search_results(_id, doc_id, doc_text, similarity)
        # Build Corpus list for use in Text sumarization. This was done here because
       →the installation of Summertime messes up my environment
        corpus_list.append(query_doc_text)
```

+
1   642   [0.9757]   the bracelet was not a true 9 the necklace perfect the bracelet nice quality just not true to length
2   45518   [0.9727]   i got this ring as a gift from my boyfriend and i love it. the only thing is that if the rings are not position correctly it pinches the skin.
+   3   37794   [0.9719]   I absolutely love this ring! I got this as my engagement ring Feb 09 This ring is beautiful and durable.
· · · · · · · · · · · · · · · · · · ·
+   4   57123   [0.9709]   I bought this as a gift for a friends birthday and she loved it. It's a beautifull ring.
+
+   5   44490   [0.9709]   I got this ring for my birthday and I love it, I cannot imagine a woman not adoring this ring.
· · · · · · · · · · · · · · · · · · ·
+   6   735   [0.9709]   I got this ring for my birthday and I love it, I cannot imagine a woman not adoring this ring.
+   7   44489   [0.9707]   my wife loves the ring, it was a great gift. extremelly cheap and high quality.
+   8   10642   [0.9706]   I love the ring and suggest every girl should have this ring in their jewelry collection.
+

+
$\mid$ 9 $\mid$ 12358 $\mid$ [0.9696] $\mid$ This was a birthday gift for my 16 YO niece. She loves the ring and was very happy to have received it. $\mid$
+++
+   10   52375   [0.9683]   This ring looks nothing like the picture. the diamonds are small and not very noticeable; I will be sending this back   ++
+
QUERY 2 - horrible bad quality bracelet
+   Rank   Doc ID   Score   Text   ++
+   Query
+
+   1   642   [0.9757]   the bracelet was not a true 9 the necklace perfect the bracelet nice quality just not true to length
+   3   37794   [0.9719]   I absolutely love this ring! I got this as my engagement ring Feb 09 This ring is beautiful and durable.
+ $\mid$ 4 $\mid$ 57123 $\mid$ [0.9709] $\mid$ I bought this as a gift for a friends birthday and she loved it. It's a beautifull ring.

++
+   8   10642   [0.9706]   I love the ring and suggest every girl should have this ring in their jewelry collection.
+   10   52375   [0.9683]   This ring looks nothing like the picture. the diamonds are small and not very noticeable; I will be sending this back   ++
<del></del>
QUERY 3 - arrived promptly and happy with the seller
+   Rank   Doc ID   Score   Text   ++

+   Query
+   1   642   [0.9757]   the bracelet was not a true 9 the necklace perfect the bracelet nice quality just not true to length
+   2   45518   [0.9727]   i got this ring as a gift from my boyfriend and i love it. the only thing is that if the rings are not position correctly it pinches the skin.
+   3   37794   [0.9719]   I absolutely love this ring! I got this as my engagement ring Feb 09 This ring is beautiful and durable.
+   5   44490   [0.9709]   I got this ring for my birthday and I love it, I cannot imagine a woman not adoring this ring.
6   735   [0.9709]   I got this ring for my birthday and I love it, I cannot imagine a woman not adoring this ring.

+
8   10642   [0.9706]   I love the ring and suggest every girl should have
this ring in their jewelry collection.
+
9   12358   [0.9696]   This was a birthday gift for my 16 YO niece. She
loves the ring and was very happy to have received it.
+
$\mid$ 10 $\mid$ 52375 $\mid$ [0.9683] $\mid$ This ring looks nothing like the picture. the
diamonds are small and not very noticeable; I will be sending this back
·
+
QUERY 4 - wear it with casual wear ++
+
Rank   Doc ID   Score   Text
++
+
Query
+
+
1   642   [0.9757]   the bracelet was not a true 9 the necklace
perfect the bracelet nice quality just not true to length
+
+
2   45518   [0.9727]   i got this ring as a gift from my boyfriend and i
love it. the only thing is that if the rings are not position correctly it
pinches the skin.
+
+
3   37794   [0.9719]   I absolutely love this ring! I got this as my
engagement ring Feb 09 This ring is beautiful and durable.

+   4   57123   [0.9709]   I bought this as a gift for a friends birthday and she loved it. It's a beautifull ring.
+   5   44490   [0.9709]   I got this ring for my birthday and I love it, I cannot imagine a woman not adoring this ring.
+   6   735   [0.9709]   I got this ring for my birthday and I love it, I cannot imagine a woman not adoring this ring.
+   7   44489   [0.9707]   my wife loves the ring, it was a great gift. extremelly cheap and high quality.
+   8   10642   [0.9706]   I love the ring and suggest every girl should have this ring in their jewelry collection.
+   9   12358   [0.9696]   This was a birthday gift for my 16 YO niece. She loves the ring and was very happy to have received it.
+   10   52375   [0.9683]   This ring looks nothing like the picture. the diamonds are small and not very noticeable; I will be sending this back
++

QUERY 5 - i expected better quality. i will return this item

++
+   Rank   Doc ID   Score   Text   ++
+   1   642   [0.9757]   the bracelet was not a true 9 the necklace perfect the bracelet nice quality just not true to length   ++
+   3   37794   [0.9719]   I absolutely love this ring! I got this as my engagement ring Feb 09 This ring is beautiful and durable.
+   4   57123   [0.9709]   I bought this as a gift for a friends birthday and she loved it. It's a beautifull ring.

+
$\mid$ 7 $\mid$ 44489 $\mid$ [0.9707] $\mid$ my wife loves the ring, it was a great gift. extremelly cheap and high quality. $\mid$
+
+   8   10642   [0.9706]   I love the ring and suggest every girl should have this ring in their jewelry collection.
+
$\mid$ 9 $\mid$ 12358 $\mid$ [0.9696] $\mid$ This was a birthday gift for my 16 YO niece. She loves the ring and was very happy to have received it. $\mid$
+
10   52375   [0.9683]   This ring looks nothing like the picture. the diamonds are small and not very noticeable; I will be sending this back
QUERY 6 - looks beautiful. The design is pretty. pefect and color is light
++
+   Rank   Doc ID   Score   Text
++
1   642   [0.9757]   the bracelet was not a true 9 the necklace perfect the bracelet nice quality just not true to length
+
+   2   45518   [0.9727]   i got this ring as a gift from my boyfriend and i

love it. the only thing is that if the rings are not position correctly it pinches the skin.
· · · · · · · · · · · · · · · · · · ·
+   3   37794   [0.9719]   I absolutely love this ring! I got this as my engagement ring Feb 09 This ring is beautiful and durable.   ++
+   4   57123   [0.9709]   I bought this as a gift for a friends birthday and she loved it. It's a beautifull ring.
+   5   44490   [0.9709]   I got this ring for my birthday and I love it, I cannot imagine a woman not adoring this ring.
+   8   10642   [0.9706]   I love the ring and suggest every girl should have this ring in their jewelry collection.
+   10   52375   [0.9683]   This ring looks nothing like the picture. the

diamonds are small and not very noticeable; I will be sending this back
<del></del>
<del>-</del>
QUERY 7 - This ring looks nothing like the picture. the diamonds are small and not very noticeable ++
+   Rank   Doc ID   Score   Text
· · · · · · · · · · · · · · · · · · ·
Query
+   1   642   [0.9757]   the bracelet was not a true 9 the necklace perfect the bracelet nice quality just not true to length   ++
+   2   45518   [0.9727]   i got this ring as a gift from my boyfriend and i love it. the only thing is that if the rings are not position correctly it pinches the skin.
+   3   37794   [0.9719]   I absolutely love this ring! I got this as my engagement ring Feb 09 This ring is beautiful and durable.
+
+   4   57123   [0.9709]   I bought this as a gift for a friends birthday and
she loved it. It's a beautifull ring.
+ $\mid$ 5 $\mid$ 44490 $\mid$ [0.9709] $\mid$ I got this ring for my birthday and I love it, I cannot imagine a woman not adoring this ring.

 ++
+   9   12358   [0.9696]   This was a birthday gift for my 16 YO niece. She loves the ring and was very happy to have received it.
+   10   52375   [0.9683]   This ring looks nothing like the picture. the diamonds are small and not very noticeable; I will be sending this back   ++
QUERY 8 - braclet looked just like its picture and is nice quality sterling silver.
+   Rank   Doc ID   Score   Text   

+
+   1   642   [0.9757]   the bracelet was not a true 9 the necklace perfect the bracelet nice quality just not true to length
+   2   45518   [0.9727]   i got this ring as a gift from my boyfriend and i love it. the only thing is that if the rings are not position correctly it pinches the skin.   ++
+   3   37794   [0.9719]   I absolutely love this ring! I got this as my engagement ring Feb 09 This ring is beautiful and durable.
4   57123   [0.9709]   I bought this as a gift for a friends birthday and she loved it. It's a beautifull ring.
5   44490   [0.9709]   I got this ring for my birthday and I love it, I cannot imagine a woman not adoring this ring.
+   6   735   [0.9709]   I got this ring for my birthday and I love it, I cannot imagine a woman not adoring this ring.
+   8   10642   [0.9706]   I love the ring and suggest every girl should have this ring in their jewelry collection.

```
+----+
| 9 | 12358 | [0.9696] | This was a birthday gift for my 16 YO niece. She loves the ring and was very happy to have received it.
|
+-----+
| 10 | 52375 | [0.9683] | This ring looks nothing like the picture. the diamonds are small and not very noticeable; I will be sending this back
|
+-----+
```

# 4 4 - Topic Modelling

```
[29]: # %%capture # !pip install bertopic
```

#### 4.1 a - Top n search results clustered them into topics

```
[31]: from bertopic import BERTopic

# # Fetch the desired number of results
n_results = int(input("Enter the number of results you want to retrieve:"))

# n_results = 65 #@param {type:"slider", min:50, max:200, step:5}
# Get the query and rank from the user using input forms

# Perform Search and retrieve the top search results
_id, doc_id, docs, similarity = search(query, n_results)
```

```
# Collect the texts from the search results
     cleaned_docs = __process_data(docs, vocab)
     # Built Topic Cluster
     topic_model = BERTopic(language="english", calculate_probabilities=True, __
      →verbose=True)
     topics, probs = topic_model.fit_transform(cleaned_docs)
     print('\n' + '='*100)
     print('Topics')
     print('='*100)
     topic_model.get_topic(0) # Select the most frequent topic
     Enter the number of results you want to retrieve:100
               0%|
                            | 0/4 [00:00<?, ?it/s]
     Batches:
     2023-03-20 04:11:03,778 - BERTopic - Transformed documents to Embeddings
     2023-03-20 04:11:12,969 - BERTopic - Reduced dimensionality
     2023-03-20 04:11:12,984 - BERTopic - Clustered reduced embeddings
     Topics
[31]: [('ring', 0.1580517209975038),
      ('rings', 0.09133390976747399),
      ('love', 0.07828620837212055),
      ('like', 0.06904416404931639),
      ('picture', 0.06826165653614105),
      ('looks', 0.06781808971865956),
      ('small', 0.05864491647817589),
      ('great', 0.05573153857006345),
      ('gift', 0.046673331192923356),
      ('one', 0.045666954883736996)]
[32]: # from bertopic import BERTopic
     # # # Fetch the desired number of results
     # n_results = int(input("Enter the number of results you want to retrieve:"))
     # # Get the query and rank from the user using input forms
     # # Perform Search and retrieve the top search results
     # _id, doc_id, docs, similarity = search(query, n_results)
```

```
# # Collect the texts from the search results
# cleaned_docs = __process_data(docs, vocab)

# # Built Topic Cluster
# topic_model = BERTopic(language="english", calculate_probabilities=True,uoverbose=True)
# topics, probs = topic_model.fit_transform(cleaned_docs)

# print('\n' + '='*100)
# print('Topics')
# print('='*100)
# topic_model.get_topic(0) # Select the most frequent topic
# topic_model.visualize_topics()
# topic_model.visualize_distribution(probs[200], min_probability=0.015)
# topic_model.visualize_barchart(top_n_topics=5)
```

```
[52]: from bertopic import BERTopic
      from umap import UMAP
      topic_object = list()
      def build_topic(docs, corpus, n_results=50):
        # Collect the texts from the search results and perform cleaning
        cleaned_docs = __process_data(docs, vocab)
        topic_model = BERTopic(language="english", calculate_probabilities=True,_
       ⇔verbose=True)
       topics, probs = topic model.fit transform(cleaned docs)
       topic_object.append(topic_model)
        # a = topic_model.get_topic(0)
        # b = topic_model.visualize_topics()
        \# c = topic\_model.visualize\_distribution(probs[n\_results], min\_probability=0.
       →0001)
        # d topics = topic model.visualize hierarchy(top n topics=n results)
        # e = topic_model.visualize_barchart(top_n_topics=n_results)
        # _topic = topic_model.get_topic(0) # Return the most frequent topics
        # _visualise = topic_model.visualize_topics()
        #_distribution = topic_model.visualize_distribution(probs[n_results],__
       ⇔min_probability=0.0001)
        # hierarchy = topic model.visualize hierarchy(top n topics=n results)
        # _terms = topic_model.visualize_barchart(top_n_topics=n_results)
        # return _topic,_visualise, _distribution, _hierachy, _terms
        return topic_object
      def build_topic2(docs, corpus, n_results=50):
```

```
n_components=7,
                        min_dist=0.0,
                        metric='cosine',
                        random_state=42)
        # Collect the texts from the search results and perform cleaning
        cleaned_docs = __process_data(docs, vocab)
        # topic_model = BERTopic(language="english", calculate_probabilities=True, ___
       \neg verbose=True)
        topic_model = BERTopic(umap_model=umap_model, language="english")
        topics, probs = topic_model.fit_transform(cleaned_docs)
        topic_object.append(topic_model)
        # a = topic_model.get_topic(0)
        # b = topic_model.visualize_topics()
        # c = topic model.visualize distribution(probs[n results], min probability=0.
       ⇔0001)
        # d_topics = topic_model.visualize_hierarchy(top_n_topics=n_results)
        # e = topic_model.visualize_barchart(top_n_topics=n_results)
        # _topic = topic_model.get_topic(0) # Return the most frequent topics
        # _visualise = topic_model.visualize_topics()
        # _distribution = topic_model.visualize_distribution(probs[n_results],__
       ⇔min_probability=0.0001)
        # _hierachy = topic_model.visualize_hierarchy(top_n_topics=n_results)
        # terms = topic model.visualize barchart(top n topics=n results)
        # return topic, visualise, distribution, hierarchy, terms
        return topic_object
      def build_viz(topic_model):
        a = topic_model.visualize_barchart(top_n_topics=5)
       b = topic_model.visualize_topics()
        # c = topic_model.visualize_distribution(probs[100], min_probability=0.0001)
        d = topic_model.visualize_hierarchy(top_n_topics=50)
        return a, b, d
[53]: # Get the query and rank from the user using input forms
      # Fetch the desired number of results
      # n results = 110 #@param {type:"slider", min:50, max:200, step:10}
      n_results = int(input("Enter the number of results you want to retrieve:"))
      # Perform Search and retrieve the top search results
      for index, query in enumerate(queries):
        _id, doc_id, docs, similarity = search(query, n_results)
```

umap\_model = UMAP(n\_neighbors=10,

```
# Build topic for the n returned result
  # a, b, c, d, e = build_topic(docs, vocab, n_results)
  topic_mod = build_topic(docs, vocab, n_results)
  print('\n' + '='*100)
  print(f'Topics for Query{index+1}: {query}')
  print('='*100)
  for topic in topic_mod:
    a = topic.get_topic(0)
  for i in a:
    print(i)
    # topic.visualize topics()
  # d_topics.get_topic(0)
Enter the number of results you want to retrieve:100
Batches:
         0%1
                     | 0/4 [00:00<?, ?it/s]
2023-03-20 04:28:27,701 - BERTopic - Transformed documents to Embeddings
2023-03-20 04:28:30,023 - BERTopic - Reduced dimensionality
2023-03-20 04:28:30,037 - BERTopic - Clustered reduced embeddings
______
===============
Topics for Query1: The ring is a great gift. My friend loves it
_____
_____
('like', 0.14433566362190403)
('quality', 0.1431988196528711)
('picture', 0.11991498508103643)
('look', 0.10939811453681614)
('item', 0.09572335021971412)
('nice', 0.09101567230288485)
('would', 0.07801343340247273)
('looked', 0.06759283814096244)
('small', 0.05987337023963492)
('looks', 0.056241834372557316)
                     | 0/4 [00:00<?, ?it/s]
Batches:
         0%1
2023-03-20 04:28:30,562 - BERTopic - Transformed documents to Embeddings
2023-03-20 04:28:33,136 - BERTopic - Reduced dimensionality
2023-03-20 04:28:33,882 - BERTopic - Clustered reduced embeddings
_____
Topics for Query2: horrible bad quality bracelet
```

```
('ring', 0.12183276766721064)
('like', 0.07357355190349747)
('love', 0.07094177580877746)
('quality', 0.06422563110494164)
('would', 0.06392440406931604)
('picture', 0.06098297988339629)
('looks', 0.051566995565807634)
('item', 0.05024508090027026)
('nice', 0.049033269567508635)
('rings', 0.04469891647111494)
         0%1
Batches:
                      | 0/4 [00:00<?, ?it/s]
2023-03-20 04:28:34,944 - BERTopic - Transformed documents to Embeddings
2023-03-20 04:28:37,239 - BERTopic - Reduced dimensionality
2023-03-20 04:28:37,606 - BERTopic - Clustered reduced embeddings
Topics for Query3: arrived promptly and happy with the seller
______
('ring', 0.18266129198040318)
('love', 0.11802913329731222)
('rings', 0.10439393232350536)
('birthday', 0.07987559243111725)
('bought', 0.07987559243111725)
('engagement', 0.07987559243111725)
('gift', 0.07586680103852315)
('got', 0.07249746109079427)
('loves', 0.06840980965378012)
('perfect', 0.054373095818095706)
                     | 0/4 [00:00<?, ?it/s]
         0%|
Batches:
2023-03-20 04:28:38,632 - BERTopic - Transformed documents to Embeddings
2023-03-20 04:28:40,929 - BERTopic - Reduced dimensionality
2023-03-20 04:28:41,610 - BERTopic - Clustered reduced embeddings
Topics for Query4: wear it with casual wear
______
=============
('ring', 0.16741287085463472)
('love', 0.1357272272144948)
('got', 0.08986440093913625)
('birthday', 0.08587515932959594)
```

```
('rings', 0.08369605746348885)
('loves', 0.07291979020160717)
('engagement', 0.06870012746367675)
('gift', 0.06527246845183929)
('beautiful', 0.062391167964256616)
('gorgeous', 0.058793973034691534)
                     | 0/4 [00:00<?, ?it/s]
Batches:
         0%1
2023-03-20 04:28:42,633 - BERTopic - Transformed documents to Embeddings
2023-03-20 04:28:44,866 - BERTopic - Reduced dimensionality
2023-03-20 04:28:45,649 - BERTopic - Clustered reduced embeddings
______
Topics for Query5: i expected better quality. i will return this item
_____
______
('ring', 0.1767252109690951)
('rings', 0.11706519938460207)
('love', 0.10631575187166697)
('like', 0.09568417668450027)
('engagement', 0.06253981636196944)
('gift', 0.0597580126473667)
('got', 0.05741446621189006)
('loves', 0.052783524245708646)
('gorgeous', 0.052783524245708646)
('silver', 0.049467585350981884)
                     | 0/4 [00:00<?, ?it/s]
Batches:
         0%1
2023-03-20 04:28:46,566 - BERTopic - Transformed documents to Embeddings
2023-03-20 04:28:49,582 - BERTopic - Reduced dimensionality
2023-03-20 04:28:50,785 - BERTopic - Clustered reduced embeddings
Topics for Query6: looks beautiful. The design is pretty. pefect and color is
light
('ring', 0.17447167112703932)
('love', 0.09487787034879627)
('rings', 0.08694488667774279)
('like', 0.07499733824066926)
('looks', 0.07416238048485875)
('picture', 0.05984590052564846)
('small', 0.05498404732650638)
```

('one', 0.05313879680946455)

```
('would', 0.04953829995403266)
('great', 0.044574857797625024)
                      | 0/4 [00:00<?, ?it/s]
Batches:
2023-03-20 04:28:51,683 - BERTopic - Transformed documents to Embeddings
2023-03-20 04:28:53,962 - BERTopic - Reduced dimensionality
2023-03-20 04:28:54,609 - BERTopic - Clustered reduced embeddings
Topics for Query7: This ring looks nothing like the picture. the diamonds are
small and not very noticeable
______
('like', 0.14613847925805665)
('picture', 0.11696714546231618)
('look', 0.09509311400165651)
('nice', 0.09190204711274937)
('looks', 0.09097746030502701)
('small', 0.0840289789573354)
('quality', 0.0827067820954791)
('ring', 0.08074483702857593)
('gold', 0.05594923597765204)
('nothing', 0.05594923597765204)
                      | 0/4 [00:00<?, ?it/s]
Batches:
          0%|
2023-03-20 04:28:55,635 - BERTopic - Transformed documents to Embeddings
2023-03-20 04:28:57,923 - BERTopic - Reduced dimensionality
2023-03-20 04:28:58,615 - BERTopic - Clustered reduced embeddings
______
Topics for Query8: braclet looked just like its picture and is nice quality
sterling silver.
------
('ring', 0.16333370068318911)
('rings', 0.0919023780855288)
('love', 0.07220901135291548)
('like', 0.06947389951020426)
('picture', 0.0686865216183162)
('looks', 0.0682401940115143)
('small', 0.0590099263317745)
('one', 0.05251564462030217)
('great', 0.04906861344537485)
('gift', 0.04696382910491251)
```

```
[54]: # viz = list()
for topic in topic_mod:
    try:
        a,b,d = build_viz(topic)
        a.show()
        b.show()
        # c.show()
        d.show()
        except ValueError: #raised if `y` is empty.
        pass

# for i in d_topics:
    # i.visualize_topics()
# topic_model.visualize_distribution(probs[200], min_probability=0.015)
```

## 4.1b - Cluster topics for each Query

```
[]: # # Feed number of n results
     # topic obj = list()
    # all_topics = set()
    # #Iterate over querys
    # for key, query in enumerate(querys):
       # Perform Search and retrieve the top search results
        _id, doc_id, docs, similarity = search(query, n_results)
        # Build topic for the n returned result for each query
        topics = build_topic(docs, vocab)
        topic_obj.append(topics)
     # print('\n' + '='*100)
        print(f"Query {key+1} - {query} ")
     # print('='*100)
        topics = topics.get_topic(0)
     # for i in range(len(topics)):
     #
         print(i)
          all\_topics.add(i[0])
```

### 4.1c - Visualize the topics

```
[]: # for topic in topic_obj:
# topic.visualize_topics()
```

#### Visualize Keywords

```
[]:  # from wordcloud import WordCloud  # import matplotlib.pyplot as plt
```

```
# # Convert the set to a space-separated string
# word_string = ' '.join(docs)
# # Create the WordCloud object
# wordcloud = WordCloud(width = 800, height = 800, background_color = 'white',
                        min_font_size = 10).generate(word_string)
# # Plot the WordCloud
# plt.figure(figsize = (8, 8), facecolor = None)
# plt.imshow(wordcloud)
# plt.axis("off")
# plt.tight_layout(pad = 0)
# # Show the plot
# plt.show()
```

#### Question 5 - Topic Summarization 5

```
Install SummerTime
```

```
[1]: # Download SummerTime
     # Swith to the Summertime directory
     !git clone https://github.com/Yale-LILY/SummerTime.git
    Cloning into 'SummerTime'...
    remote: Enumerating objects: 4385, done.
    remote: Counting objects: 100% (655/655), done.
    remote: Compressing objects: 100% (185/185), done.
    remote: Total 4385 (delta 568), reused 470 (delta 470), pack-reused 3730
    Receiving objects: 100% (4385/4385), 9.84 MiB | 21.21 MiB/s, done.
    Resolving deltas: 100% (2406/2406), done.
[2]: %cd SummerTime/
     # Pip install Summertime locally
     !pip install -e .
    /content/SummerTime
    Looking in indexes: https://pypi.org/simple, https://us-python.pkg.dev/colab-
    wheels/public/simple/
    Obtaining file:///content/SummerTime
      Installing build dependencies ... done
      Checking if build backend supports build editable ... done
      Getting requirements to build wheel ... done
      Preparing metadata (pyproject.toml) ... done
```

```
Collecting gensim~=3.8.3
  Downloading gensim-3.8.3.tar.gz (23.4 MB)
                           23.4/23.4 MB
35.2 MB/s eta 0:00:00
  Preparing metadata (setup.py) ... done
Requirement already satisfied: sentencepiece~=0.1.95 in
/usr/local/lib/python3.9/dist-packages (from summertime==1.2.1) (0.1.97)
Collecting lexrank~=0.1.0
 Downloading lexrank-0.1.0-py3-none-any.whl (69 kB)
                            69.8/69.8 KB
11.9 MB/s eta 0:00:00
Collecting tensorboard~=2.4.1
  Downloading tensorboard-2.4.1-py3-none-any.whl (10.6 MB)
                           10.6/10.6 MB
77.6 MB/s eta 0:00:00
Requirement already satisfied: prettytable in
/usr/local/lib/python3.9/dist-packages (from summertime==1.2.1) (3.6.0)
Collecting flake8
  Downloading flake8-6.0.0-py2.py3-none-any.whl (57 kB)
                           57.8/57.8 KB
10.1 MB/s eta 0:00:00
Collecting or ison
  Downloading orjson-3.8.7-cp39-cp39-manylinux_2_28_x86_64.whl (140 kB)
                          140.9/140.9 KB
22.9 MB/s eta 0:00:00
Requirement already satisfied: beautifulsoup4 in
/usr/local/lib/python3.9/dist-packages (from summertime==1.2.1) (4.9.3)
Collecting pytextrank
  Downloading pytextrank-3.2.4-py3-none-any.whl (30 kB)
Requirement already satisfied: cython in /usr/local/lib/python3.9/dist-packages
(from summertime==1.2.1) (0.29.33)
Collecting datasets~=1.6.2
  Downloading datasets-1.6.2-py3-none-any.whl (221 kB)
                          221.8/221.8 KB
33.3 MB/s eta 0:00:00
Collecting black~=21.12b0
  Downloading black-21.12b0-py3-none-any.whl (156 kB)
                          156.7/156.7 KB
24.4 MB/s eta 0:00:00
Collecting py7zr~=0.16.1
 Downloading py7zr-0.16.4-py3-none-any.whl (67 kB)
                           67.7/67.7 KB
11.5 MB/s eta 0:00:00
Collecting gdown~=4.2.0
  Downloading gdown-4.2.2.tar.gz (13 kB)
  Installing build dependencies ... done
  Getting requirements to build wheel ... done
 Preparing metadata (pyproject.toml) ... done
```

```
Collecting easynmt~=2.0.1
  Downloading EasyNMT-2.0.2.tar.gz (23 kB)
  Preparing metadata (setup.py) ... done
Collecting readability-lxml
  Downloading readability lxml-0.8.1-py3-none-any.whl (20 kB)
Collecting jupyter
  Downloading jupyter-1.0.0-py2.py3-none-any.whl (2.7 kB)
Collecting progressbar
  Downloading progressbar-2.5.tar.gz (10 kB)
  Preparing metadata (setup.py) ... done
Collecting transformers~=4.5.1
  Downloading transformers-4.5.1-py3-none-any.whl (2.1 MB)
                           2.1/2.1 MB
92.4 MB/s eta 0:00:00
Collecting sklearn
  Downloading sklearn-0.0.post1.tar.gz (3.6 kB)
  Preparing metadata (setup.py) ... done
Collecting tqdm~=4.49.0
  Downloading tqdm-4.49.0-py2.py3-none-any.whl (69 kB)
                           69.8/69.8 KB
11.5 MB/s eta 0:00:00
Requirement already satisfied: torch~=1.8 in
/usr/local/lib/python3.9/dist-packages (from summertime==1.2.1) (1.13.1+cu116)
Collecting fasttext~=0.9.2
 Downloading fasttext-0.9.2.tar.gz (68 kB)
                           68.8/68.8 KB
12.3 MB/s eta 0:00:00
  Preparing metadata (setup.py) ... done
Collecting click==7.1.2
  Downloading click-7.1.2-py2.py3-none-any.whl (82 kB)
                           82.8/82.8 KB
13.1 MB/s eta 0:00:00
Collecting nltk==3.6.2
 Downloading nltk-3.6.2-py3-none-any.whl (1.5 MB)
                           1.5/1.5 MB
81.6 MB/s eta 0:00:00
Collecting spacy==3.0.6
 Downloading spacy-3.0.6-cp39-cp39-manylinux2014_x86_64.whl (12.6 MB)
                           12.6/12.6 MB
84.3 MB/s eta 0:00:00
Requirement already satisfied: numpy in /usr/local/lib/python3.9/dist-
packages (from summertime==1.2.1) (1.22.4)
Collecting summ-eval==0.70
  Downloading summ_eval-0.70-py3-none-any.whl (62.5 MB)
                           62.5/62.5 MB
7.3 MB/s eta 0:00:00
Requirement already satisfied: regex in /usr/local/lib/python3.9/dist-
packages (from nltk==3.6.2->summertime==1.2.1) (2022.6.2)
```

```
Requirement already satisfied: joblib in /usr/local/lib/python3.9/dist-packages
(from nltk==3.6.2->summertime==1.2.1) (1.1.1)
Requirement already satisfied: wasabi<1.1.0,>=0.8.1 in
/usr/local/lib/python3.9/dist-packages (from spacy==3.0.6->summertime==1.2.1)
(0.10.1)
Requirement already satisfied: pathy>=0.3.5 in /usr/local/lib/python3.9/dist-
packages (from spacy==3.0.6->summertime==1.2.1) (0.10.1)
Requirement already satisfied: blis<0.8.0,>=0.4.0 in
/usr/local/lib/python3.9/dist-packages (from spacy==3.0.6->summertime==1.2.1)
(0.7.9)
Requirement already satisfied: requests<3.0.0,>=2.13.0 in
/usr/local/lib/python3.9/dist-packages (from spacy==3.0.6->summertime==1.2.1)
(2.25.1)
Requirement already satisfied: jinja2 in /usr/local/lib/python3.9/dist-packages
(from spacy==3.0.6->summertime==1.2.1) (3.1.2)
Requirement already satisfied: spacy-legacy<3.1.0,>=3.0.4 in
/usr/local/lib/python3.9/dist-packages (from spacy==3.0.6->summertime==1.2.1)
Requirement already satisfied: srsly<3.0.0,>=2.4.1 in
/usr/local/lib/python3.9/dist-packages (from spacy==3.0.6->summertime==1.2.1)
Requirement already satisfied: murmurhash<1.1.0,>=0.28.0 in
/usr/local/lib/python3.9/dist-packages (from spacy==3.0.6->summertime==1.2.1)
(1.0.9)
Collecting typer<0.4.0,>=0.3.0
  Downloading typer-0.3.2-py3-none-any.whl (21 kB)
Requirement already satisfied: catalogue<2.1.0,>=2.0.3 in
/usr/local/lib/python3.9/dist-packages (from spacy==3.0.6->summertime==1.2.1)
Requirement already satisfied: setuptools in /usr/local/lib/python3.9/dist-
packages (from spacy==3.0.6->summertime==1.2.1) (63.4.3)
Requirement already satisfied: cymem<2.1.0,>=2.0.2 in
/usr/local/lib/python3.9/dist-packages (from spacy==3.0.6->summertime==1.2.1)
(2.0.7)
Collecting pydantic<1.8.0,>=1.7.1
 Downloading pydantic-1.7.4-cp39-cp39-manylinux2014_x86_64.whl (10.3 MB)
                           10.3/10.3 MB
117.5 MB/s eta 0:00:00
Requirement already satisfied: preshed<3.1.0,>=3.0.2 in
/usr/local/lib/python3.9/dist-packages (from spacy==3.0.6->summertime==1.2.1)
(3.0.8)
Collecting thinc<8.1.0,>=8.0.3
  Downloading
thinc-8.0.17-cp39-cp39-manylinux 2_17_x86_64.manylinux2014_x86_64.whl (668 kB)
                          668.8/668.8 KB
62.6 MB/s eta 0:00:00
Requirement already satisfied: packaging>=20.0 in
/usr/local/lib/python3.9/dist-packages (from spacy==3.0.6->summertime==1.2.1)
```

```
(23.0)
Collecting pyemd==0.5.1
  Downloading pyemd-0.5.1.tar.gz (91 kB)
                           91.5/91.5 KB
14.4 MB/s eta 0:00:00
  Preparing metadata (setup.py) ... done
Requirement already satisfied: gin-config in /usr/local/lib/python3.9/dist-
packages (from summ-eval==0.70->summertime==1.2.1) (0.5.0)
Collecting bert-score
  Downloading bert_score-0.3.13-py3-none-any.whl (61 kB)
                           61.1/61.1 KB
8.9 MB/s eta 0:00:00
Requirement already satisfied: psutil in /usr/local/lib/python3.9/dist-
packages (from summ-eval==0.70->summertime==1.2.1) (5.4.8)
Collecting pytorch-pretrained-bert
  Downloading pytorch_pretrained_bert-0.6.2-py3-none-any.whl (123 kB)
                          123.8/123.8 KB
20.6 MB/s eta 0:00:00
Collecting moverscore
  Downloading moverscore-1.0.3.tar.gz (7.7 kB)
  Preparing metadata (setup.py) ... done
Requirement already satisfied: scipy in /usr/local/lib/python3.9/dist-packages
(from summ-eval==0.70->summertime==1.2.1) (1.10.1)
Requirement already satisfied: six in /usr/local/lib/python3.9/dist-packages
(from summ-eval==0.70->summertime==1.2.1) (1.15.0)
Collecting sacremoses
  Downloading sacremoses-0.0.53.tar.gz (880 kB)
                          880.6/880.6 KB
70.8 MB/s eta 0:00:00
  Preparing metadata (setup.py) ... done
Collecting wmd
  Downloading wmd-1.3.2.tar.gz (104 kB)
                          104.6/104.6 KB
18.0 MB/s eta 0:00:00
  Preparing metadata (setup.py) ... done
Collecting blanc
  Downloading blanc-0.3.0-py3-none-any.whl (29 kB)
Requirement already satisfied: networkx in /usr/local/lib/python3.9/dist-
packages (from summ-eval==0.70->summertime==1.2.1) (3.0)
Collecting sacrebleu
  Downloading sacrebleu-2.3.1-py3-none-any.whl (118 kB)
                          118.9/118.9 KB
20.5 MB/s eta 0:00:00
Collecting stanza
  Downloading stanza-1.5.0-py3-none-any.whl (802 kB)
                          802.5/802.5 KB
66.8 MB/s eta 0:00:00
Requirement already satisfied: platformdirs>=2 in
```

```
/usr/local/lib/python3.9/dist-packages (from black~=21.12b0->summertime==1.2.1)
(3.1.1)
Requirement already satisfied: typing-extensions>=3.10.0.0 in
/usr/local/lib/python3.9/dist-packages (from black~=21.12b0->summertime==1.2.1)
(4.5.0)
Collecting mypy-extensions>=0.4.3
  Downloading mypy_extensions-1.0.0-py3-none-any.whl (4.7 kB)
Collecting pathspec<1,>=0.9.0
 Downloading pathspec-0.11.1-py3-none-any.whl (29 kB)
Collecting tomli<2.0.0,>=0.2.6
  Downloading tomli-1.2.3-py3-none-any.whl (12 kB)
Collecting multiprocess
  Downloading multiprocess-0.70.14-py39-none-any.whl (132 kB)
                          132.9/132.9 KB
22.9 MB/s eta 0:00:00
Collecting xxhash
 Downloading
xxhash-3.2.0-cp39-cp39-manylinux_2_17_x86_64.manylinux2014_x86_64.whl (212 kB)
                           212.2/212.2
KB 1.0 MB/s eta 0:00:00
Collecting huggingface-hub<0.1.0
  Downloading huggingface_hub-0.0.19-py3-none-any.whl (56 kB)
                           56.9/56.9 KB
8.8 MB/s eta 0:00:00
Requirement already satisfied: fsspec in /usr/local/lib/python3.9/dist-
packages (from datasets~=1.6.2->summertime==1.2.1) (2023.3.0)
Collecting dill
 Downloading dill-0.3.6-py3-none-any.whl (110 kB)
                          110.5/110.5 KB
17.6 MB/s eta 0:00:00
Requirement already satisfied: pandas in /usr/local/lib/python3.9/dist-
packages (from datasets~=1.6.2->summertime==1.2.1) (1.4.4)
Requirement already satisfied: pyarrow>=1.0.0<4.0.0 in
/usr/local/lib/python3.9/dist-packages (from datasets~=1.6.2->summertime==1.2.1)
(9.0.0)
Requirement already satisfied: protobuf in /usr/local/lib/python3.9/dist-
packages (from easynmt~=2.0.1->summertime==1.2.1) (3.19.6)
Collecting pybind11>=2.2
 Using cached pybind11-2.10.4-py3-none-any.whl (222 kB)
Requirement already satisfied: filelock in /usr/local/lib/python3.9/dist-
packages (from gdown~=4.2.0->summertime==1.2.1) (3.9.1)
Requirement already satisfied: smart_open>=1.8.1 in
/usr/local/lib/python3.9/dist-packages (from gensim~=3.8.3->summertime==1.2.1)
(6.3.0)
Collecting urlextract>=0.7
  Downloading urlextract-1.8.0-py3-none-any.whl (21 kB)
Collecting path.py>=10.5
```

```
Downloading path.py-12.5.0-py3-none-any.whl (2.3 kB)
Requirement already satisfied: pyrsistent>=0.14.0 in
/usr/local/lib/python3.9/dist-packages (from lexrank~=0.1.0->summertime==1.2.1)
(0.19.3)
Collecting pyppmd>=0.17.0
 Downloading
pyppmd-1.0.0-cp39-cp39-manylinux_2_17_x86_64.manylinux2014_x86_64.whl (138 kB)
                          138.7/138.7 KB
23.1 MB/s eta 0:00:00
Collecting brotli>=1.0.9
  Downloading Brotli-1.0.9-cp39-cp39-manylinux1_x86_64.whl (357 kB)
                          357.2/357.2 KB
46.2 MB/s eta 0:00:00
Collecting pybcj>=0.5.0
  Downloading
pybcj-1.0.1-cp39-cp39-manylinux_2_17_x86_64.manylinux2014_x86_64.whl (49 kB)
                           49.6/49.6 KB
7.7 MB/s eta 0:00:00
Collecting multivolumefile>=0.2.3
  Downloading multivolumefile-0.2.3-py3-none-any.whl (17 kB)
Collecting pyzstd>=0.14.4
 Downloading
pyzstd-0.15.4-cp39-cp39-manylinux_2_17_x86_64.manylinux2014_x86_64.whl (384 kB)
                          384.0/384.0 KB
45.8 MB/s eta 0:00:00
Collecting texttable
  Downloading texttable-1.6.7-py2.py3-none-any.whl (10 kB)
Collecting pycryptodomex>=3.6.6
  Downloading
pycryptodomex-3.17-cp35-abi3-manylinux_2_17_x86_64.manylinux2014_x86_64.whl (2.1
MB)
                           2.1/2.1 MB
94.4 MB/s eta 0:00:00
Requirement already satisfied: werkzeug>=0.11.15 in
/usr/local/lib/python3.9/dist-packages (from
tensorboard~=2.4.1->summertime==1.2.1) (2.2.3)
Requirement already satisfied: markdown>=2.6.8 in /usr/local/lib/python3.9/dist-
packages (from tensorboard~=2.4.1->summertime==1.2.1) (3.4.1)
Requirement already satisfied: absl-py>=0.4 in /usr/local/lib/python3.9/dist-
packages (from tensorboard~=2.4.1->summertime==1.2.1) (1.4.0)
Collecting google-auth<2,>=1.6.3
 Downloading google_auth-1.35.0-py2.py3-none-any.whl (152 kB)
                          152.9/152.9 KB
23.3 MB/s eta 0:00:00
Requirement already satisfied: google-auth-oauthlib<0.5,>=0.4.1 in
/usr/local/lib/python3.9/dist-packages (from
tensorboard~=2.4.1->summertime==1.2.1) (0.4.6)
Requirement already satisfied: wheel>=0.26 in /usr/local/lib/python3.9/dist-
```

```
packages (from tensorboard~=2.4.1->summertime==1.2.1) (0.40.0)
Requirement already satisfied: tensorboard-plugin-wit>=1.6.0 in
/usr/local/lib/python3.9/dist-packages (from
tensorboard~=2.4.1->summertime==1.2.1) (1.8.1)
Requirement already satisfied: grpcio>=1.24.3 in /usr/local/lib/python3.9/dist-
packages (from tensorboard~=2.4.1->summertime==1.2.1) (1.51.3)
Collecting tokenizers<0.11,>=0.10.1
 Downloading tokenizers-0.10.3-cp39-cp39-manylinux_2_5_x86_64.manylinux1_x86_64
.manylinux_2_12_x86_64.manylinux2010_x86_64.whl (3.3 MB)
                           3.3/3.3 MB
103.8 MB/s eta 0:00:00
Requirement already satisfied: soupsieve>1.2 in
/usr/local/lib/python3.9/dist-packages (from beautifulsoup4->summertime==1.2.1)
(2.4)
Collecting pycodestyle<2.11.0,>=2.10.0
 Downloading pycodestyle-2.10.0-py2.py3-none-any.whl (41 kB)
                           41.3/41.3 KB
7.1 MB/s eta 0:00:00
Collecting mccabe<0.8.0,>=0.7.0
  Downloading mccabe-0.7.0-py2.py3-none-any.whl (7.3 kB)
Collecting pyflakes<3.1.0,>=3.0.0
 Downloading pyflakes-3.0.1-py2.py3-none-any.whl (62 kB)
                           62.8/62.8 KB
11.8 MB/s eta 0:00:00
Requirement already satisfied: ipywidgets in
/usr/local/lib/python3.9/dist-packages (from jupyter->summertime==1.2.1) (7.7.1)
Requirement already satisfied: jupyter-console in /usr/local/lib/python3.9/dist-
packages (from jupyter->summertime==1.2.1) (6.1.0)
Collecting qtconsole
  Downloading qtconsole-5.4.1-py3-none-any.whl (120 kB)
                          120.9/120.9 KB
20.4 MB/s eta 0:00:00
Requirement already satisfied: ipykernel in /usr/local/lib/python3.9/dist-
packages (from jupyter->summertime==1.2.1) (5.3.4)
Requirement already satisfied: nbconvert in /usr/local/lib/python3.9/dist-
packages (from jupyter->summertime==1.2.1) (6.5.4)
Requirement already satisfied: notebook in /usr/local/lib/python3.9/dist-
packages (from jupyter->summertime==1.2.1) (6.3.0)
Requirement already satisfied: wcwidth in /usr/local/lib/python3.9/dist-packages
(from prettytable->summertime==1.2.1) (0.2.6)
Collecting pygments>=2.7.4
  Downloading Pygments-2.14.0-py3-none-any.whl (1.1 MB)
                           1.1/1.1 MB
85.4 MB/s eta 0:00:00
Collecting icecream>=2.1
  Downloading icecream-2.1.3-py2.py3-none-any.whl (8.4 kB)
Collecting graphviz>=0.13
 Downloading graphviz-0.20.1-py3-none-any.whl (47 kB)
```

#### 47.0/47.0 KB

## 8.3 MB/s eta 0:00:00 Requirement already satisfied: chardet in /usr/local/lib/python3.9/distpackages (from readability-lxml->summertime==1.2.1) (4.0.0) Collecting cssselect Downloading cssselect-1.2.0-py2.py3-none-any.whl (18 kB) Requirement already satisfied: lxml in /usr/local/lib/python3.9/dist-packages (from readability-lxml->summertime==1.2.1) (4.9.2) Requirement already satisfied: rsa<5,>=3.1.4 in /usr/local/lib/python3.9/distpackages (from google-auth<2,>=1.6.3->tensorboard~=2.4.1->summertime==1.2.1) (4.9)Collecting cachetools<5.0,>=2.0.0 Downloading cachetools-4.2.4-py3-none-any.whl (10 kB) Requirement already satisfied: pyasn1-modules>=0.2.1 in /usr/local/lib/python3.9/dist-packages (from googleauth<2,>=1.6.3->tensorboard~=2.4.1->summertime==1.2.1) (0.2.8) Requirement already satisfied: requests-oauthlib>=0.7.0 in /usr/local/lib/python3.9/dist-packages (from google-authoauthlib<0.5,>=0.4.1->tensorboard~=2.4.1->summertime==1.2.1) (1.3.1) Requirement already satisfied: pyyaml in /usr/local/lib/python3.9/dist-packages (from huggingface-hub<0.1.0->datasets~=1.6.2->summertime==1.2.1) (6.0) Collecting executing>=0.3.1 Downloading executing-1.2.0-py2.py3-none-any.whl (24 kB) Collecting colorama>=0.3.9 Downloading colorama-0.4.6-py2.py3-none-any.whl (25 kB) Collecting asttokens>=2.0.1 Downloading asttokens-2.2.1-py2.py3-none-any.whl (26 kB) Requirement already satisfied: importlib-metadata>=4.4 in /usr/local/lib/python3.9/dist-packages (from markdown>=2.6.8->tensorboard~=2.4.1->summertime==1.2.1) (6.0.0) Requirement already satisfied: matplotlib>=3.4 in /usr/local/lib/python3.9/distpackages (from networkx->summ-eval==0.70->summertime==1.2.1) (3.7.1) Requirement already satisfied: pytz>=2020.1 in /usr/local/lib/python3.9/distpackages (from pandas->datasets~=1.6.2->summertime==1.2.1) (2022.7.1) Requirement already satisfied: python-dateutil>=2.8.1 in /usr/local/lib/python3.9/dist-packages (from pandas->datasets~=1.6.2->summertime==1.2.1) (2.8.2) Collecting path Downloading path-16.6.0-py3-none-any.whl (26 kB) Requirement already satisfied: certifi>=2017.4.17 in /usr/local/lib/python3.9/dist-packages (from requests<3.0.0,>=2.13.0->spacy==3.0.6->summertime==1.2.1) (2022.12.7) Requirement already satisfied: urllib3<1.27,>=1.21.1 in /usr/local/lib/python3.9/dist-packages (from requests<3.0.0,>=2.13.0->spacy==3.0.6->summertime==1.2.1) (1.26.15) Requirement already satisfied: idna<3,>=2.5 in /usr/local/lib/python3.9/dist-

packages (from requests<3.0.0,>=2.13.0->spacy==3.0.6->summertime==1.2.1) (2.10)

Collecting uritools

```
Downloading uritools-4.0.1-py3-none-any.whl (10 kB)
Requirement already satisfied: MarkupSafe>=2.1.1 in
/usr/local/lib/python3.9/dist-packages (from
werkzeug>=0.11.15->tensorboard~=2.4.1->summertime==1.2.1) (2.1.2)
Requirement already satisfied: ipython>=5.0.0 in /usr/local/lib/python3.9/dist-
packages (from ipykernel->jupyter->summertime==1.2.1) (7.9.0)
Requirement already satisfied: jupyter-client in /usr/local/lib/python3.9/dist-
packages (from ipykernel->jupyter->summertime==1.2.1) (6.1.12)
Requirement already satisfied: traitlets>=4.1.0 in
/usr/local/lib/python3.9/dist-packages (from
ipykernel->jupyter->summertime==1.2.1) (5.7.1)
Requirement already satisfied: tornado>=4.2 in /usr/local/lib/python3.9/dist-
packages (from ipykernel->jupyter->summertime==1.2.1) (6.2)
Requirement already satisfied: jupyterlab-widgets>=1.0.0 in
/usr/local/lib/python3.9/dist-packages (from
ipywidgets->jupyter->summertime==1.2.1) (3.0.5)
Requirement already satisfied: widgetsnbextension~=3.6.0 in
/usr/local/lib/python3.9/dist-packages (from
ipywidgets->jupyter->summertime==1.2.1) (3.6.2)
Requirement already satisfied: ipython-genutils~=0.2.0 in
/usr/local/lib/python3.9/dist-packages (from
ipywidgets->jupyter->summertime==1.2.1) (0.2.0)
Requirement already satisfied: prompt-toolkit!=3.0.0,!=3.0.1,<3.1.0,>=2.0.0 in
/usr/local/lib/python3.9/dist-packages (from jupyter-
console->jupyter->summertime==1.2.1) (2.0.10)
Collecting typing
  Downloading typing-3.7.4.3.tar.gz (78 kB)
                           78.6/78.6 KB
11.5 MB/s eta 0:00:00
  Preparing metadata (setup.py) ... done
Collecting portalocker
  Downloading portalocker-2.7.0-py2.py3-none-any.whl (15 kB)
Requirement already satisfied: entrypoints>=0.2.2 in
/usr/local/lib/python3.9/dist-packages (from
nbconvert->jupyter->summertime==1.2.1) (0.4)
Requirement already satisfied: mistune<2,>=0.8.1 in
/usr/local/lib/python3.9/dist-packages (from
nbconvert->jupyter->summertime==1.2.1) (0.8.4)
Requirement already satisfied: bleach in /usr/local/lib/python3.9/dist-packages
(from nbconvert->jupyter->summertime==1.2.1) (6.0.0)
Requirement already satisfied: defusedxml in /usr/local/lib/python3.9/dist-
packages (from nbconvert->jupyter->summertime==1.2.1) (0.7.1)
Requirement already satisfied: nbclient>=0.5.0 in /usr/local/lib/python3.9/dist-
packages (from nbconvert->jupyter->summertime==1.2.1) (0.7.2)
Requirement already satisfied: jupyter-core>=4.7 in
/usr/local/lib/python3.9/dist-packages (from
nbconvert->jupyter->summertime==1.2.1) (5.2.0)
Requirement already satisfied: jupyterlab-pygments in
```

```
/usr/local/lib/python3.9/dist-packages (from
nbconvert->jupyter->summertime==1.2.1) (0.2.2)
Requirement already satisfied: nbformat>=5.1 in /usr/local/lib/python3.9/dist-
packages (from nbconvert->jupyter->summertime==1.2.1) (5.7.3)
Requirement already satisfied: pandocfilters>=1.4.1 in
/usr/local/lib/python3.9/dist-packages (from
nbconvert->jupyter->summertime==1.2.1) (1.5.0)
Requirement already satisfied: tinycss2 in /usr/local/lib/python3.9/dist-
packages (from nbconvert->jupyter->summertime==1.2.1) (1.2.1)
Requirement already satisfied: pyzmq>=17 in /usr/local/lib/python3.9/dist-
packages (from notebook->jupyter->summertime==1.2.1) (23.2.1)
Requirement already satisfied: Send2Trash>=1.5.0 in
/usr/local/lib/python3.9/dist-packages (from
notebook->jupyter->summertime==1.2.1) (1.8.0)
Requirement already satisfied: argon2-cffi in /usr/local/lib/python3.9/dist-
packages (from notebook->jupyter->summertime==1.2.1) (21.3.0)
Requirement already satisfied: terminado>=0.8.3 in
/usr/local/lib/python3.9/dist-packages (from
notebook->jupyter->summertime==1.2.1) (0.17.1)
Requirement already satisfied: prometheus-client in
/usr/local/lib/python3.9/dist-packages (from
notebook->jupyter->summertime==1.2.1) (0.16.0)
Collecting boto3
 Downloading boto3-1.26.93-py3-none-any.whl (135 kB)
                          135.1/135.1 KB
20.6 MB/s eta 0:00:00
Collecting qtpy>=2.0.1
  Downloading QtPy-2.3.0-py3-none-any.whl (83 kB)
                           83.6/83.6 KB
14.0 MB/s eta 0:00:00
Requirement already satisfied: PySocks!=1.5.7,>=1.5.6 in
/usr/local/lib/python3.9/dist-packages (from
requests<3.0.0,>=2.13.0->spacy=3.0.6->summertime==1.2.1) (1.7.1)
Requirement already satisfied: tabulate>=0.8.9 in /usr/local/lib/python3.9/dist-
packages (from sacrebleu->summ-eval==0.70->summertime==1.2.1) (0.8.10)
Collecting emoji
 Downloading emoji-2.2.0.tar.gz (240 kB)
                          240.9/240.9 KB
27.0 MB/s eta 0:00:00
 Preparing metadata (setup.py) ... done
Requirement already satisfied: zipp>=0.5 in /usr/local/lib/python3.9/dist-
packages (from importlib-
metadata>=4.4->markdown>=2.6.8->tensorboard~=2.4.1->summertime==1.2.1) (3.15.0)
Requirement already satisfied: decorator in /usr/local/lib/python3.9/dist-
packages (from ipython>=5.0.0->ipykernel->jupyter->summertime==1.2.1) (4.4.2)
Requirement already satisfied: pickleshare in /usr/local/lib/python3.9/dist-
packages (from ipython>=5.0.0->ipykernel->jupyter->summertime==1.2.1) (0.7.5)
Collecting jedi>=0.10
```

```
Downloading jedi-0.18.2-py2.py3-none-any.whl (1.6 MB)
                           1.6/1.6 MB
85.9 MB/s eta 0:00:00
Requirement already satisfied: backcall in /usr/local/lib/python3.9/dist-
packages (from ipython>=5.0.0->ipykernel->jupyter->summertime==1.2.1) (0.2.0)
Requirement already satisfied: pexpect in /usr/local/lib/python3.9/dist-packages
(from ipython>=5.0.0->ipykernel->jupyter->summertime==1.2.1) (4.8.0)
Requirement already satisfied: pillow>=6.2.0 in /usr/local/lib/python3.9/dist-
packages (from matplotlib>=3.4->networkx->summ-eval==0.70->summertime==1.2.1)
(8.4.0)
Requirement already satisfied: pyparsing>=2.3.1 in
/usr/local/lib/python3.9/dist-packages (from matplotlib>=3.4->networkx->summ-
eval==0.70->summertime==1.2.1) (3.0.9)
Requirement already satisfied: fonttools>=4.22.0 in
/usr/local/lib/python3.9/dist-packages (from matplotlib>=3.4->networkx->summ-
eval==0.70->summertime==1.2.1) (4.39.0)
Requirement already satisfied: importlib-resources>=3.2.0 in
/usr/local/lib/python3.9/dist-packages (from matplotlib>=3.4->networkx->summ-
eval==0.70->summertime==1.2.1) (5.12.0)
Requirement already satisfied: contourpy>=1.0.1 in
/usr/local/lib/python3.9/dist-packages (from matplotlib>=3.4->networkx->summ-
eval==0.70->summertime==1.2.1) (1.0.7)
Requirement already satisfied: cycler>=0.10 in /usr/local/lib/python3.9/dist-
packages (from matplotlib>=3.4->networkx->summ-eval==0.70->summertime==1.2.1)
(0.11.0)
Requirement already satisfied: kiwisolver>=1.0.1 in
/usr/local/lib/python3.9/dist-packages (from matplotlib>=3.4->networkx->summ-
eval==0.70->summertime==1.2.1) (1.4.4)
Requirement already satisfied: fastjsonschema in /usr/local/lib/python3.9/dist-
packages (from nbformat>=5.1->nbconvert->jupyter->summertime==1.2.1) (2.16.3)
Requirement already satisfied: jsonschema>=2.6 in /usr/local/lib/python3.9/dist-
packages (from nbformat>=5.1->nbconvert->jupyter->summertime==1.2.1) (4.3.3)
Requirement already satisfied: pyasn1<0.5.0,>=0.4.6 in
/usr/local/lib/python3.9/dist-packages (from pyasn1-modules>=0.2.1->google-
auth<2,>=1.6.3->tensorboard~=2.4.1->summertime==1.2.1) (0.4.8)
Requirement already satisfied: oauthlib>=3.0.0 in /usr/local/lib/python3.9/dist-
packages (from requests-oauthlib>=0.7.0->google-auth-
oauthlib<0.5,>=0.4.1->tensorboard\sim=2.4.1->summertime==1.2.1) (3.2.2)
Requirement already satisfied: ptyprocess in /usr/local/lib/python3.9/dist-
packages (from terminado>=0.8.3->notebook->jupyter->summertime==1.2.1) (0.7.0)
Requirement already satisfied: argon2-cffi-bindings in
/usr/local/lib/python3.9/dist-packages (from
argon2-cffi->notebook->jupyter->summertime==1.2.1) (21.2.0)
Requirement already satisfied: webencodings in /usr/local/lib/python3.9/dist-
packages (from bleach->nbconvert->jupyter->summertime==1.2.1) (0.5.1)
Collecting jmespath<2.0.0,>=0.7.1
  Downloading jmespath-1.0.1-py3-none-any.whl (20 kB)
```

Collecting botocore<1.30.0,>=1.29.93

```
Downloading botocore-1.29.93-py3-none-any.whl (10.5 MB)
                           10.5/10.5 MB
120.3 MB/s eta 0:00:00
Collecting s3transfer<0.7.0,>=0.6.0
  Downloading s3transfer-0.6.0-py3-none-any.whl (79 kB)
                           79.6/79.6 KB
9.8 MB/s eta 0:00:00
Requirement already satisfied: parso<0.9.0,>=0.8.0 in
/usr/local/lib/python3.9/dist-packages (from
jedi>=0.10->ipython>=5.0.0->ipykernel->jupyter->summertime==1.2.1) (0.8.3)
Requirement already satisfied: attrs>=17.4.0 in /usr/local/lib/python3.9/dist-
packages (from
jsonschema>=2.6->nbformat>=5.1->nbconvert->jupyter->summertime==1.2.1) (22.2.0)
Requirement already satisfied: cffi>=1.0.1 in /usr/local/lib/python3.9/dist-
packages (from argon2-cffi-
bindings->argon2-cffi->notebook->jupyter->summertime==1.2.1) (1.15.1)
Requirement already satisfied: pycparser in /usr/local/lib/python3.9/dist-
packages (from cffi>=1.0.1->argon2-cffi-
bindings->argon2-cffi->notebook->jupyter->summertime==1.2.1) (2.21)
Building wheels for collected packages: pyemd, easynmt, fasttext, gdown, gensim,
progressbar, sklearn, moverscore, sacremoses, wmd, emoji, typing
  Building wheel for pyemd (setup.py) ... done
  Created wheel for pyemd: filename=pyemd-0.5.1-cp39-cp39-linux_x86_64.whl
size=541000
sha256=41d9009d609648622c879cc676f79aeecf92052e802499021d28d5f070c913e0
  Stored in directory: /root/.cache/pip/wheels/64/bf/3e/0859be9a0108fc932a29b943
792dcafb3b979555cf1bb5add6
  Building wheel for easynmt (setup.py) ... done
  Created wheel for easynmt: filename=EasyNMT-2.0.2-py3-none-any.whl size=19920
sha256=3bbd29f2805318d2eca63e3620cb6b2b9adf918eb221fdcc07083f53fbc46799
  Stored in directory: /root/.cache/pip/wheels/26/53/00/5761f3b9bf6af87bdbc44029
2a4eb98a6afb25823dd76fca26
  Building wheel for fasttext (setup.py) ... done
  Created wheel for fasttext: filename=fasttext-0.9.2-cp39-cp39-linux_x86_64.whl
size=4395649
sha256=d976f43c4bd9a6d3445652fe322dbb1bf6b58e01b6d753b4024a059248721a42
  Stored in directory: /root/.cache/pip/wheels/64/57/bc/1741406019061d5664914b07
0bd3e71f6244648732bc96109e
  Building wheel for gdown (pyproject.toml) ... done
  Created wheel for gdown: filename=gdown-4.2.2-py3-none-any.whl size=14495
\verb|sha| 256 = 06f71219467600b6e42eddc87ebcca57a2ffda 15d666bba6889ebf28d9dbd6ab||
  Stored in directory: /root/.cache/pip/wheels/d3/d1/f3/112c8482aa998cd2fbf9d0c8
fd3a15b06a5581ca43152878c9
  Building wheel for gensim (setup.py) ... done
  Created wheel for gensim: filename=gensim-3.8.3-cp39-cp39-linux_x86_64.whl
size=26528072
sha256=19f6c19b178741e613fa000a7b7392d2796763e67641d6c11fd76fc441f9e0d9
  Stored in directory: /root/.cache/pip/wheels/ca/5d/af/618594ec2f28608c1d6ee7d2
```

b7e95a3e9b06551e3b80a491d6

Building wheel for progressbar (setup.py) ... done

Created wheel for progressbar: filename=progressbar-2.5-py3-none-any.whl size=12080

 $\verb|sha| 256 = \verb|cf97f9f57a| 2b01fe01c59647f6c87da| 006c3b60329a9eada| 35b678a55e233799|$ 

Stored in directory: /root/.cache/pip/wheels/d7/d9/89/a3f31c76ff6d51dc3b157562 8f59afe59e4ceae3f2748cd7ad

Building wheel for sklearn (setup.py) ... done

Created wheel for sklearn: filename=sklearn-0.0.post1-py3-none-any.whl size=2955

sha256=795f8056572345f67a7edff1688dbcdd1c5ccf9f48edea0a340adea692a1527a

Stored in directory: /root/.cache/pip/wheels/f8/e0/3d/9d0c2020c44a519b9f02ab4fa6d2a4a996c98d79ab2f569fa1

Building wheel for moverscore (setup.py) ... done

Created wheel for moverscore: filename=moverscore-1.0.3-py3-none-any.whl size=7963

sha256=26224f12c0f102ecc9a33025170ba8c912487cedc8e178df2eab943e9821f917

Stored in directory: /root/.cache/pip/wheels/ec/c2/18/826e61ab6e3989b946b3dea3 45711552870ce9096209c9378c

Building wheel for sacremoses (setup.py) ... done

Created wheel for sacremoses: filename=sacremoses-0.0.53-py3-none-any.whl size=895259

sha256=419729c9474ec987729cc6ee3dc22a3d00a07b1810ea23f3cd2324726641afcf

Stored in directory: /root/.cache/pip/wheels/12/1c/3d/46cf06718d63a32ff798a895 94b61e7f345ab6b36d909ce033

Building wheel for wmd (setup.py) ... done

Created wheel for wmd: filename=wmd-1.3.2-cp39-cp39-linux\_x86\_64.whl size=1230902

Stored in directory: /root/.cache/pip/wheels/f2/bb/7b/46bc1b99fbd5018b8cfeb75e6ffaa9d64c0bcecc026a5514b6

Building wheel for emoji (setup.py) ... done

Created wheel for emoji: filename=emoji-2.2.0-py3-none-any.whl size=234926 sha256=c3c875f89a9e124d9fd95bd4c14970f0111a6ffdd7e964fb90dad0aa42948a06

Stored in directory: /root/.cache/pip/wheels/9a/b8/0f/f580817231cbf59f6ade9fd1 32ff60ada1de9f7dc85521f857

Building wheel for typing (setup.py) ... done

Created wheel for typing: filename=typing-3.7.4.3-py3-none-any.whl size=26321 sha256=c922349a7022cbbb03c2ce8469d072fe7a088233213935176ea6a42d9ea6469f

Stored in directory: /root/.cache/pip/wheels/fa/17/1f/332799f975d1b2d7f9b3f33bbccf65031e794717d24432caee

Successfully built pyemd easynmt fasttext gdown gensim progressbar sklearn moverscore sacremoses wmd emoji typing

Installing collected packages: tokenizers, texttable, sklearn, progressbar, executing, brotli, xxhash, wmd, uritools, typing, tqdm, tomli, qtpy, pyzstd, pyppmd, pygments, pyflakes, pyemd, pydantic, pycryptodomex, pycodestyle, pybind11, pybcj, portalocker, pathspec, path, orjson, mypy-extensions, multivolumefile, mccabe, jmespath, jedi, graphviz, emoji, dill, cssselect,

colorama, click, cachetools, asttokens, urlextract, typer, thinc, stanza, sacremoses, sacrebleu, readability-lxml, py7zr, path.py, nltk, multiprocess, moverscore, icecream, huggingface-hub, google-auth, gensim, flake8, fasttext, botocore, black, transformers, s3transfer, lexrank, gdown, datasets, tensorboard, spacy, qtconsole, easynmt, boto3, blanc, bert-score, pytorchpretrained-bert, pytextrank, summ-eval, jupyter, summertime Attempting uninstall: tokenizers Found existing installation: tokenizers 0.13.2 Uninstalling tokenizers-0.13.2: Successfully uninstalled tokenizers-0.13.2 Attempting uninstall: tqdm Found existing installation: tqdm 4.65.0 Uninstalling tqdm-4.65.0: Successfully uninstalled tqdm-4.65.0 Attempting uninstall: tomli Found existing installation: tomli 2.0.1 Uninstalling tomli-2.0.1: Successfully uninstalled tomli-2.0.1 Attempting uninstall: pygments Found existing installation: Pygments 2.6.1 Uninstalling Pygments-2.6.1: Successfully uninstalled Pygments-2.6.1 Attempting uninstall: pydantic Found existing installation: pydantic 1.10.6 Uninstalling pydantic-1.10.6: Successfully uninstalled pydantic-1.10.6 Attempting uninstall: graphviz Found existing installation: graphviz 0.10.1 Uninstalling graphviz-0.10.1: Successfully uninstalled graphviz-0.10.1 Attempting uninstall: click Found existing installation: click 8.1.3 Uninstalling click-8.1.3: Successfully uninstalled click-8.1.3 Attempting uninstall: cachetools Found existing installation: cachetools 5.3.0 Uninstalling cachetools-5.3.0: Successfully uninstalled cachetools-5.3.0 Attempting uninstall: typer Found existing installation: typer 0.7.0 Uninstalling typer-0.7.0: Successfully uninstalled typer-0.7.0 Attempting uninstall: thinc Found existing installation: thinc 8.1.9 Uninstalling thinc-8.1.9: Successfully uninstalled thinc-8.1.9 Attempting uninstall: nltk

Found existing installation: nltk 3.7

Uninstalling nltk-3.7: Successfully uninstalled nltk-3.7 Attempting uninstall: huggingface-hub Found existing installation: huggingface-hub 0.13.2 Uninstalling huggingface-hub-0.13.2: Successfully uninstalled huggingface-hub-0.13.2 Attempting uninstall: google-auth Found existing installation: google-auth 2.16.2 Uninstalling google-auth-2.16.2: Successfully uninstalled google-auth-2.16.2 Attempting uninstall: gensim Found existing installation: gensim 3.6.0 Uninstalling gensim-3.6.0: Successfully uninstalled gensim-3.6.0 Attempting uninstall: transformers Found existing installation: transformers 4.27.1 Uninstalling transformers-4.27.1: Successfully uninstalled transformers-4.27.1 Attempting uninstall: gdown Found existing installation: gdown 4.4.0 Uninstalling gdown-4.4.0: Successfully uninstalled gdown-4.4.0 Attempting uninstall: tensorboard Found existing installation: tensorboard 2.11.2 Uninstalling tensorboard-2.11.2: Successfully uninstalled tensorboard-2.11.2 Attempting uninstall: spacy Found existing installation: spacy 3.4.4 Uninstalling spacy-3.4.4: Successfully uninstalled spacy-3.4.4 Running setup.py develop for summertime

ERROR: pip's dependency resolver does not currently take into account all the packages that are installed. This behaviour is the source of the following dependency conflicts.

tensorflow 2.11.0 requires tensorboard<2.12,>=2.11, but you have tensorboard 2.4.1 which is incompatible.

sentence-transformers 2.2.2 requires huggingface-hub>=0.4.0, but you have huggingface-hub 0.0.19 which is incompatible.

sentence-transformers 2.2.2 requires transformers<5.0.0,>=4.6.0, but you have transformers 4.5.1 which is incompatible.

pandas-profiling 3.2.0 requires pydantic>=1.8.1, but you have pydantic 1.7.4 which is incompatible.

google-api-core 2.11.0 requires google-auth<3.0dev,>=2.14.1, but you have google-auth 1.35.0 which is incompatible.

flask 2.2.3 requires click>=8.0, but you have click 7.1.2 which is incompatible. en-core-web-sm 3.4.1 requires spacy<3.5.0,>=3.4.0, but you have spacy 3.0.6 which is incompatible.

Successfully installed asttokens-2.2.1 bert-score-0.3.13 black-21.12b0 blanc-0.3.0 boto3-1.26.93 botocore-1.29.93 brotli-1.0.9 cachetools-4.2.4 click-7.1.2 colorama-0.4.6 cssselect-1.2.0 datasets-1.6.2 dill-0.3.6 easynmt-2.0.2 emoji-2.2.0 executing-1.2.0 fasttext-0.9.2 flake8-6.0.0 gdown-4.2.2 gensim-3.8.3 google-auth-1.35.0 graphviz-0.20.1 huggingfacehub-0.0.19 icecream-2.1.3 jedi-0.18.2 jmespath-1.0.1 jupyter-1.0.0 lexrank-0.1.0 mccabe-0.7.0 moverscore-1.0.3 multiprocess-0.70.14 multivolumefile-0.2.3 mypyextensions-1.0.0 nltk-3.6.2 orjson-3.8.7 path-16.6.0 path.py-12.5.0 pathspec-0.11.1 portalocker-2.7.0 progressbar-2.5 py7zr-0.16.4 pybcj-1.0.1 pybind11-2.10.4 pycodestyle-2.10.0 pycryptodomex-3.17 pydantic-1.7.4 pyemd-0.5.1 pyflakes-3.0.1 pygments-2.14.0 pyppmd-1.0.0 pytextrank-3.2.4 pytorch-pretrainedbert-0.6.2 pyzstd-0.15.4 qtconsole-5.4.1 qtpy-2.3.0 readability-lxml-0.8.1 s3transfer-0.6.0 sacrebleu-2.3.1 sacremoses-0.0.53 sklearn-0.0.post1 spacy-3.0.6 stanza-1.5.0 summ-eval-0.70 summertime-1.2.1 tensorboard-2.4.1 texttable-1.6.7 thinc-8.0.17 tokenizers-0.10.3 tomli-1.2.3 tqdm-4.49.0 transformers-4.5.1 typer-0.3.2 typing-3.7.4.3 uritools-4.0.1 urlextract-1.8.0 wmd-1.3.2 xxhash-3.2.0

#### [3]: ## Finish setup

# Setup ROUGE (needed to use ROUGE evaluation metric)

!export ROUGE\_HOME=/usr/local/bin/python/dist-packages/summ\_eval/ROUGE-1.5.5/
!pip install -U git+https://github.com/bheinzerling/pyrouge.git

```
Looking in indexes: https://pypi.org/simple, https://us-python.pkg.dev/colab-
    wheels/public/simple/
    Collecting git+https://github.com/bheinzerling/pyrouge.git
      Cloning https://github.com/bheinzerling/pyrouge.git to /tmp/pip-req-
    build-f0knsiz6
      Running command git clone --filter=blob:none --quiet
    https://github.com/bheinzerling/pyrouge.git /tmp/pip-req-build-f0knsiz6
      Resolved https://github.com/bheinzerling/pyrouge.git to commit
    08e9cc35d713f718a05b02bf3bb2e29947d436ce
      Preparing metadata (setup.py) ... done
    Building wheels for collected packages: pyrouge
      Building wheel for pyrouge (setup.py) ... done
      Created wheel for pyrouge: filename=pyrouge-0.1.3-py3-none-any.whl size=191923
    sha256=a189fa525d0b988fc288a012fc237bd4329780c4b845c1d5025f285b006fc9a8
      Stored in directory: /tmp/pip-ephem-wheel-cache-
    na8zjyo2/wheels/bd/07/80/f241050743bda1488efce41793a0b5502c97888adf191110d3
    Successfully built pyrouge
    Installing collected packages: pyrouge
    Successfully installed pyrouge-0.1.3
[4]: # If you've been prompted to restart the kernel in either of the two cells
     ⇔above,
     # Please do so
     # Then run this cell to go back to the relevant directory
     %cd /content/SummerTime/
     # !pip install en core web sm==3.0.0
     !python -m spacy download en_core_web_sm
    /content/SummerTime
    2023-03-17 10:31:37.530741: I tensorflow/core/platform/cpu_feature_guard.cc:193]
    This TensorFlow binary is optimized with oneAPI Deep Neural Network Library
    (oneDNN) to use the following CPU instructions in performance-critical
    operations: AVX2 AVX512F AVX512 VNNI FMA
    To enable them in other operations, rebuild TensorFlow with the appropriate
    compiler flags.
    2023-03-17 10:31:37.681080: I tensorflow/core/util/port.cc:104] oneDNN custom
    operations are on. You may see slightly different numerical results due to
    floating-point round-off errors from different computation orders. To turn them
    off, set the environment variable `TF_ENABLE_ONEDNN_OPTS=0`.
    2023-03-17 10:31:38.443168: W
    tensorflow/compiler/xla/stream_executor/platform/default/dso_loader.cc:64] Could
    not load dynamic library 'libnvinfer.so.7'; dlerror: libnvinfer.so.7: cannot
    open shared object file: No such file or directory; LD_LIBRARY_PATH:
    /usr/lib64-nvidia
    2023-03-17 10:31:38.443269: W
```

tensorflow/compiler/xla/stream\_executor/platform/default/dso\_loader.cc:64] Could not load dynamic library 'libnvinfer\_plugin.so.7'; dlerror: libnvinfer\_plugin.so.7: cannot open shared object file: No such file or directory; LD\_LIBRARY\_PATH: /usr/lib64-nvidia 2023-03-17 10:31:38.443288: W tensorflow/compiler/tf2tensorrt/utils/py\_utils.cc:38] TF-TRT Warning: Cannot dlopen some TensorRT libraries. If you would like to use Nvidia GPU with TensorRT, please make sure the missing libraries mentioned above are installed properly. Looking in indexes: https://pypi.org/simple, https://us-python.pkg.dev/colabwheels/public/simple/ Collecting en-core-web-sm==3.0.0 Downloading https://github.com/explosion/spacymodels/releases/download/en\_core\_web\_sm-3.0.0/en\_core\_web\_sm-3.0.0-py3-noneany.whl (13.7 MB) 13.7/13.7 MB 42.5 MB/s eta 0:00:00 Requirement already satisfied: spacy<3.1.0,>=3.0.0 in /usr/local/lib/python3.9/dist-packages (from en-core-web-sm==3.0.0) (3.0.6) Requirement already satisfied: preshed<3.1.0,>=3.0.2 in /usr/local/lib/python3.9/dist-packages (from spacy<3.1.0,>=3.0.0->en-core-websm==3.0.0) (3.0.8) Requirement already satisfied: numpy>=1.15.0 in /usr/local/lib/python3.9/distpackages (from spacy<3.1.0,>=3.0.0->en-core-web-sm==3.0.0) (1.22.4) Requirement already satisfied: requests<3.0.0,>=2.13.0 in /usr/local/lib/python3.9/dist-packages (from spacy<3.1.0,>=3.0.0->en-core-websm==3.0.0) (2.25.1) Requirement already satisfied: tqdm<5.0.0,>=4.38.0 in /usr/local/lib/python3.9/dist-packages (from spacy<3.1.0,>=3.0.0->en-core-websm==3.0.0) (4.49.0) Requirement already satisfied: pydantic<1.8.0,>=1.7.1 in /usr/local/lib/python3.9/dist-packages (from spacy<3.1.0,>=3.0.0->en-core-websm==3.0.0) (1.7.4) Requirement already satisfied: thinc<8.1.0,>=8.0.3 in /usr/local/lib/python3.9/dist-packages (from spacy<3.1.0,>=3.0.0->en-core-websm==3.0.0) (8.0.17) Requirement already satisfied: typer<0.4.0,>=0.3.0 in /usr/local/lib/python3.9/dist-packages (from spacy<3.1.0,>=3.0.0->en-core-websm==3.0.0) (0.3.2)Requirement already satisfied: spacy-legacy<3.1.0,>=3.0.4 in /usr/local/lib/python3.9/dist-packages (from spacy<3.1.0,>=3.0.0->en-core-websm==3.0.0) (3.0.12) Requirement already satisfied: cymem<2.1.0,>=2.0.2 in /usr/local/lib/python3.9/dist-packages (from spacy<3.1.0,>=3.0.0->en-core-websm==3.0.0) (2.0.7) Requirement already satisfied: setuptools in /usr/local/lib/python3.9/distpackages (from spacy<3.1.0,>=3.0.0->en-core-web-sm==3.0.0) (63.4.3)

Requirement already satisfied: pathy>=0.3.5 in /usr/local/lib/python3.9/dist-

```
packages (from spacy<3.1.0,>=3.0.0->en-core-web-sm==3.0.0) (0.10.1)
Requirement already satisfied: murmurhash<1.1.0,>=0.28.0 in
/usr/local/lib/python3.9/dist-packages (from spacy<3.1.0,>=3.0.0->en-core-web-
sm==3.0.0) (1.0.9)
Requirement already satisfied: blis<0.8.0,>=0.4.0 in
/usr/local/lib/python3.9/dist-packages (from spacy<3.1.0,>=3.0.0->en-core-web-
sm==3.0.0) (0.7.9)
Requirement already satisfied: wasabi<1.1.0,>=0.8.1 in
/usr/local/lib/python3.9/dist-packages (from spacy<3.1.0,>=3.0.0->en-core-web-
sm==3.0.0) (0.10.1)
Requirement already satisfied: jinja2 in /usr/local/lib/python3.9/dist-packages
(from spacy<3.1.0,>=3.0.0->en-core-web-sm==3.0.0) (3.1.2)
Requirement already satisfied: catalogue<2.1.0,>=2.0.3 in
/usr/local/lib/python3.9/dist-packages (from spacy<3.1.0,>=3.0.0->en-core-web-
sm==3.0.0) (2.0.8)
Requirement already satisfied: packaging>=20.0 in /usr/local/lib/python3.9/dist-
packages (from spacy<3.1.0,>=3.0.0->en-core-web-sm==3.0.0) (23.0)
Requirement already satisfied: srsly<3.0.0,>=2.4.1 in
/usr/local/lib/python3.9/dist-packages (from spacy<3.1.0,>=3.0.0->en-core-web-
sm==3.0.0) (2.4.6)
Requirement already satisfied: smart-open<7.0.0,>=5.2.1 in
/usr/local/lib/python3.9/dist-packages (from
pathy>=0.3.5->spacy<3.1.0,>=3.0.0->en-core-web-sm==3.0.0) (6.3.0)
Requirement already satisfied: urllib3<1.27,>=1.21.1 in
/usr/local/lib/python3.9/dist-packages (from
requests<3.0.0,>=2.13.0->spacy<3.1.0,>=3.0.0->en-core-web-sm==3.0.0) (1.26.15)
Requirement already satisfied: idna<3,>=2.5 in /usr/local/lib/python3.9/dist-
packages (from requests<3.0.0,>=2.13.0->spacy<3.1.0,>=3.0.0->en-core-web-
sm==3.0.0) (2.10)
Requirement already satisfied: chardet<5,>=3.0.2 in
/usr/local/lib/python3.9/dist-packages (from
requests<3.0.0,>=2.13.0->spacy<3.1.0,>=3.0.0->en-core-web-sm==3.0.0) (4.0.0)
Requirement already satisfied: certifi>=2017.4.17 in
/usr/local/lib/python3.9/dist-packages (from
requests<3.0.0,>=2.13.0->spacy<3.1.0,>=3.0.0->en-core-web-sm==3.0.0) (2022.12.7)
Requirement already satisfied: click<7.2.0,>=7.1.1 in
/usr/local/lib/python3.9/dist-packages (from
typer<0.4.0,>=0.3.0->spacy<3.1.0,>=3.0.0->en-core-web-sm==3.0.0) (7.1.2)
Requirement already satisfied: MarkupSafe>=2.0 in /usr/local/lib/python3.9/dist-
packages (from jinja2->spacy<3.1.0,>=3.0.0->en-core-web-sm==3.0.0) (2.1.2)
Installing collected packages: en-core-web-sm
  Attempting uninstall: en-core-web-sm
    Found existing installation: en-core-web-sm 3.4.1
   Uninstalling en-core-web-sm-3.4.1:
      Successfully uninstalled en-core-web-sm-3.4.1
Successfully installed en-core-web-sm-3.0.0
 Download and installation successful
You can now load the package via spacy.load('en_core_web_sm')
```

## [5]: !pip install --upgrade transformers

```
Looking in indexes: https://pypi.org/simple, https://us-python.pkg.dev/colab-
wheels/public/simple/
Requirement already satisfied: transformers in /usr/local/lib/python3.9/dist-
packages (4.5.1)
Collecting transformers
 Using cached transformers-4.27.1-py3-none-any.whl (6.7 MB)
Requirement already satisfied: tqdm>=4.27 in /usr/local/lib/python3.9/dist-
packages (from transformers) (4.49.0)
Collecting huggingface-hub<1.0,>=0.11.0
  Using cached huggingface_hub-0.13.2-py3-none-any.whl (199 kB)
Requirement already satisfied: filelock in /usr/local/lib/python3.9/dist-
packages (from transformers) (3.9.1)
Requirement already satisfied: pyyaml>=5.1 in /usr/local/lib/python3.9/dist-
packages (from transformers) (6.0)
Requirement already satisfied: packaging>=20.0 in /usr/local/lib/python3.9/dist-
packages (from transformers) (23.0)
Requirement already satisfied: requests in /usr/local/lib/python3.9/dist-
packages (from transformers) (2.25.1)
Collecting tokenizers!=0.11.3,<0.14,>=0.11.1
 Using cached
tokenizers-0.13.2-cp39-cp39-manylinux_2_17_x86_64.manylinux2014_x86_64.whl (7.6
Requirement already satisfied: regex!=2019.12.17 in
/usr/local/lib/python3.9/dist-packages (from transformers) (2022.6.2)
Requirement already satisfied: numpy>=1.17 in /usr/local/lib/python3.9/dist-
packages (from transformers) (1.22.4)
Requirement already satisfied: typing-extensions>=3.7.4.3 in
/usr/local/lib/python3.9/dist-packages (from huggingface-
hub<1.0,>=0.11.0->transformers) (4.5.0)
Requirement already satisfied: chardet<5,>=3.0.2 in
/usr/local/lib/python3.9/dist-packages (from requests->transformers) (4.0.0)
Requirement already satisfied: certifi>=2017.4.17 in
/usr/local/lib/python3.9/dist-packages (from requests->transformers) (2022.12.7)
Requirement already satisfied: idna<3,>=2.5 in /usr/local/lib/python3.9/dist-
packages (from requests->transformers) (2.10)
Requirement already satisfied: urllib3<1.27,>=1.21.1 in
/usr/local/lib/python3.9/dist-packages (from requests->transformers) (1.26.15)
Installing collected packages: tokenizers, huggingface-hub, transformers
  Attempting uninstall: tokenizers
    Found existing installation: tokenizers 0.10.3
   Uninstalling tokenizers-0.10.3:
      Successfully uninstalled tokenizers-0.10.3
  Attempting uninstall: huggingface-hub
    Found existing installation: huggingface-hub 0.0.19
    Uninstalling huggingface-hub-0.0.19:
```

```
Successfully uninstalled huggingface-hub-0.0.19
Attempting uninstall: transformers
Found existing installation: transformers 4.5.1
Uninstalling transformers-4.5.1:
Successfully uninstalled transformers-4.5.1
ERROR: pip's dependency resolver does not currently take into account all the packages that are installed. This behaviour is the source of the following dependency conflicts.
datasets 1.6.2 requires huggingface-hub<0.1.0, but you have huggingface-hub
0.13.2 which is incompatible.
summertime 1.2.1 requires transformers~=4.5.1, but you have transformers 4.27.1 which is incompatible.
Successfully installed huggingface-hub-0.13.2 tokenizers-0.13.2 transformers-4.27.1
```

#### Implement Summarization

```
[6]: def build query embedding(query, n):
       query_doc = pd.Series(query)
       with torch.no_grad():
           # Tokenization
           tokenized = query_doc[0:n].apply((lambda x: tokenizer.encode(x,__
      →add_special_tokens=True)))
           # padding
           \max len = 0
           q = 0
           for i in tokenized.values:
               # BERT only accept maximum 512 values
               if len(i) > 512:
                   temp = tokenized.values[q]
                   tokenized.values[q] = temp[:512]
                   i = tokenized.values[q]
                   print('too much tokenized.values for BERT, only 512 are taken')
               # print(len(i))
               if len(i) > max_len:
                   max_len = len(i)
               q += 1
           padded = np.array([i + [0]*(max_len-len(i)) for i in tokenized.values])
           np.array(padded).shape
           # masking
```

```
attention_mask = np.where(padded != 0, 1, 0)
      attention_mask.shape
      # run the model
      input_ids = torch.tensor(padded)
      attention_mask = torch.tensor(attention_mask)
      last_hidden_states = model(input_ids, attention_mask=attention_mask)
      query_features = last_hidden_states[0][:,0,:].numpy()
     return query_features
from prettytable import PrettyTable, ALL
def search(query, n_results=5):
  # Get the query embedding using the BERT-based model
 embedding = build_query_embedding(query, n_results)
  # Calculate the cosine similarity between the query embedding and the
 ⇔document embeddings
 similarity = cosine_similarity(train_features, embedding)
 # Get the indexes of the top n_results most similar documents sorted by \sqcup
 ⇔similarity score
 indexes = np.argsort(similarity, axis=None)[::-1][:n results]
 # Get the document IDs, texts, and similarity scores of the top n results \Box
 ⇔most similar documents
 d id = [i for i in indexes]
 ndoc id = [data.iloc[k]['ID'] for k in indexes]
 ndoc_text = [data.iloc[k]['Reviews'] for k in indexes]
 similarity_scores = [np.around(similarity[k], 4) for k in indexes]
  # Return the query IDs, document IDs, document texts, and similarity scores
 return d_id, ndoc_id, ndoc_text, similarity_scores
def print search results(d_id, ndoc_id, ndoc_text, similarity_scores):
  # Create a PrettyTable object to format the search results
 results = PrettyTable()
  # Set the field names and formatting options for the table
 results.field_names = ["Rank", "Doc ID", "Score", "Text"]
 results.hrules = ALL
 results.vrules = ALL
 results.align["Rank"] = "c"
 results.align["Doc ID"] = "1"
 results.align["Similarity Score"] = "c"
 results.align["Text"] = "1"
```

```
results.float_format = ".4"

# Add the query as the first row of the table
results.add_row(["Query", "", query])

# Add the top n_results most similar documents to the table
for i in range(n_results):
    results.add_row([i+1, ndoc_id[i], similarity_scores[i], ndoc_text[i]])

# Print the formatted table
print(results)
```

```
[43]: from summertime import model
      # corpus = corpus_list
      summary_list = list()
      for key, corpus in enumerate(corpus list):
        print('\n' + f"QUERY {key+1} SUMMARIES")
       lexrank = model.LexRankModel(corpus)
        # # Inference
       summary = lexrank.summarize(corpus)
       summary_list.append(summary)
       for i in range(len(summary)):
          print("Summary Review %d: "%(i+1), summary[i])
      # Get the query and rank from the user using input forms
      # Fetch the desired number of results
      # Add the top n_results most similar documents to the table
      # for i in range(n results):
      # results.add_row([i+1, ndoc_id[i], similarity_scores[i], ndoc_text[i]])
      # Longformer2Roberta
      # longformer = model.LongformerModel()
      # longformer_summary = longformer.summarize(corpus)
      # for i in range(len(longformer_summary)):
        print("\nSummary Review %d: "%(i+1), longformer_summary[i])
```

#### QUERY 1 SUMMARIES

Summary Review 1: extremelly cheap and high quality. my wife loves the ring, it was a great gift.

Summary Review 2: It's a beautifull ring. I bought this as a gift for a friends birthday and she loved it.

Summary Review 3: Thank you, Dorothy Eve's Addiction was wonderful with sending the ring and the ring is beautiful; my daughter waas thrilled with the ring.

Summary Review 4: It closes firmly with a clic and has a classic look. The look is very beautiful with a smooth finish.

Summary Review 5: I love the ring and suggest every girl should have this ring in their jewelry collection.

Summary Review 6: I would recommend this amethyst ring to anyone who is in the market for a reasonably priced amethyst ring. This ring is just absolutely stunning and beautiful!

Summary Review 7: I wanted to know if this ring is like 2 rings in one, because this ring is beyond gorgeous, I just love it.

Summary Review 8: I wanted to know if this ring is like 2 rings in one, because this ring is beyond gorgeous, I just love it.

Summary Review 9: She loves the ring and was very happy to have received it. This was a birthday gift for my 16 YO niece.

Summary Review 10: The ring shines perfectly I love this ring! This ring is perfect I say why spend thousands when you don't have to?

#### QUERY 2 SUMMARIES

Summary Review 1: :) :) I like it.

Summary Review 2: great way to support the local pro sports team without wearing an oversized jersey or a hat to mess up the hair

Summary Review 3: Very disappointed in the appearance and quality of the bracelet and its definitely not worth \$45.00 - not even close.

Summary Review 4: Other than that a great very comfortable ring. my only wish on this ring is- I wish the cut potrion went all the way around the ring.

Summary Review 5: its what i wanted :) but its not my favorite piercing of mine but i have to wear the bioplast cuz i break out with certain metals

Summary Review 6: the product came very fast and was just like how amazon explained itthe ring is very clearly written NO WAR and thick which i likebut i guess if you like small rings this isnt your ring

Summary Review 7: Just what I was looking for. It is so pretty and dainty.

Summary Review 8: Will definately reccommend Eve's Addiction to all my friends and family. I was very pleased with the quality of this item.

Summary Review 9: The ring is pretty enough, but the metal of the ring is very insubstantial it pushes in very easily.

Summary Review 10: I just got these yesterday as a Christmas gift- so far they look just like the picture and seem very nice.

#### QUERY 3 SUMMARIES

Summary Review 1: I'm very happy with it and recommend it unreservedly. Item was great quality and came promptly.

Summary Review 2: the product came very fast and was just like how amazon explained itthe ring is very clearly written NO WAR and thick which i likebut i guess if you like small rings this isnt your ring

Summary Review 3: Very disappointed in the appearance and quality of the bracelet and its definitely not worth \$45.00 - not even close.

Summary Review 4: great way to support the local pro sports team without

wearing an oversized jersey or a hat to mess up the hair

Summary Review 5: Recv'd my ring in a timely manner it looks very antique would recommend this ring to any garnet lover!

Summary Review 6: It was described perfectly and was everything I had hoped The product arrived in a very short period of time and was perfect.

Summary Review 7: the product i recieved was nice it came in a timley matter faster than i expected will order this item again

Summary Review 8: Other than that a great very comfortable ring. my only wish on this ring is- I wish the cut potrion went all the way around the ring.

Summary Review 9: Just what I was looking for. It is so pretty and dainty.

Summary Review 10: It closes firmly with a clic and has a classic look. The look is very beautiful with a smooth finish.

#### QUERY 4 SUMMARIES

Summary Review 1: very good for everyday wear or dressing up

Summary Review 2: very dressy ery suitable for wearing for fashionable occasions.

Summary Review 3: They are very comfortable. These are nice to wear when you want something casual to wear.

Summary Review 4: I wear on the weekends or out & about but isn't not suited for my work or my going out events This pendant I classify as the best for casual wear.

Summary Review 5: The stones catch the light and the style is very comfortable to wear. It is so unique and a pleasure to wear.

Summary Review 6: its what i wanted :) but its not my favorite piercing of mine but i have to wear the bioplast cuz i break out with certain metals

Summary Review 7: I have been told that the ring is very comfortable to wear and he was quite surprised and please to see the Masonic ring in titanium.

Summary Review 8: :) :) I like it.

Summary Review 9: great way to support the local pro sports team without wearing an oversized jersey or a hat to mess up the hair

Summary Review 10: ! This pinis nice enough to wear in formal occasions. Wear it with pride!

#### QUERY 5 SUMMARIES

Summary Review 1: You can see all the keys, any flute fan would adore having this item. The flute charm is so detailed and is of very high quality.

Summary Review 2: It is too small for an adult. This is an attractive and high quality item for a young teenager.

Summary Review 3: I have been told that the ring is very comfortable to wear and he was quite surprised and please to see the Masonic ring in titanium.

Summary Review 4: The diamond had a crack in one Garnet and another one had a large chip.

Summary Review 5: I love the ring and suggest every girl should have this ring in their jewelry collection.

Summary Review 6: great way to support the local pro sports team without wearing an oversized jersey or a hat to mess up the hair

Summary Review 7: Very flimsy. I would not recommend this item The quality and

look were not what I had anticipated.

Summary Review 8: Recv'd my ring in a timely manner it looks very antique would recommend this ring to any garnet lover!

Summary Review 9: the product i recieved was nice it came in a timley matter faster than i expected will order this item again

Summary Review 10: the product came very fast and was just like how amazon explained itthe ring is very clearly written NO WAR and thick which i likebut i guess if you like small rings this isnt your ring

#### QUERY 6 SUMMARIES

Summary Review 1: I bought it for my aunt as a present and the color is very nice. The message is very positive and it looks very pretty.

Summary Review 2: The silver does not look as in the picture but just like polished silver. the earrings are as in the picture, stones look good and are light and comfortable, reasonable quality for the price.

Summary Review 3: This medical alert braclet looked just like its picture and is nice quality sterling silver.

Summary Review 4: Although the picture looks like metal beads and description states sterling silver, these are pearls.

Summary Review 5: CAN BE LAYED FOR A BEAUTIFUL LOOK. YET IT IS VERY PRETTY.

Summary Review 6: A truly beautiful piece to own. The workmanship is excellent and the details are beautiful.

Summary Review 7: From the picture they looked to have some purple in them but they are clear just like the title says.

Summary Review 8: The color of the stones is rich and beautiful. The ring is exactly as pictured and looks very pretty on my hand.

Summary Review 9: I've seen them elsewhere for quite a high price and these are beautiful. They are very colorful and you know they are turtles.

Summary Review 10: This ring is alot smaller in person than in pictures, the pictures make it look like the diamonds are decent size and they are very small, I was a little disappointed.

#### QUERY 7 SUMMARIES

Summary Review 1: The diamond had a crack in one Garnet and another one had a large chip.

Summary Review 2: The ring was nice and looked like picture but had a crack in one Garnet and another one had a large chip.

Summary Review 3: the diamonds are small and not very noticeable; I will be sending this back This ring looks nothing like the picture.

Summary Review 4: Although the picture looks like metal beads and description states sterling silver, these are pearls.

Summary Review 5: This ring is alot smaller in person than in pictures, the pictures make it look like the diamonds are decent size and they are very small, I was a little disappointed.

Summary Review 6: I ended up returning the bracelet because I have amethyst jewelry and it was extremely poor quality. The stones on this bracelet are extremely pale, more pink than purple.

Summary Review 7: From the picture they looked to have some purple in them but

they are clear just like the title says.

Summary Review 8: This medical alert braclet looked just like its picture and is nice quality sterling silver.

Summary Review 9: The diamonds are flawed more than a little bit. I didn't like this product because the diamonds looked nothing like the picture.

Summary Review 10: the product came very fast and was just like how amazon explained itthe ring is very clearly written NO WAR and thick which i likebut i guess if you like small rings this isnt your ring

#### QUERY 8 SUMMARIES

Summary Review 1: This medical alert braclet looked just like its picture and is nice quality sterling silver.

Summary Review 2: The silver does not look as in the picture but just like polished silver. the earnings are as in the picture, stones look good and are light and comfortable, reasonable quality for the price.

Summary Review 3: Although the picture looks like metal beads and description states sterling silver, these are pearls.

Summary Review 4: I ended up returning the bracelet because I have amethyst jewelry and it was extremely poor quality. The stones on this bracelet are extremely pale, more pink than purple.

Summary Review 5: A must for everyone who is a Tiger fan and owns an Italian Charm Bracelet. Very nice quality.

Summary Review 6: Really looks like the picture. Silver is nicely finished and the enamel is a nice highlight.

Summary Review 7: It is an amazing price for such a beautiful pendant. It picks up the colors of your clothing.

Summary Review 8: The silver and black enamel cross ring speaks for its self. Utterly undescibable. Many have ask where to purchase the ring so they to can share their inner feelings in an outward way without having to say a work, but allow the ring to speak for them.

Summary Review 9: The ring was nice and looked like picture but had a crack in one Garnet and another one had a large chip.

Summary Review 10: I bought it for my aunt as a present and the color is very nice. The message is very positive and it looks very pretty.

#### 5a - Evaluation

```
[44]: _values = list()

for i, value in enumerate(corpus_list):
    _values.append(value[0])
    print(f"{i+1} - {value[0]}")
```

- 1 my wife loves the ring, it was a great gift. extremelly cheap and high quality.
- 2 It is as nice as it looks on the picture. :) I like it. :)
- 3 Item was great quality and came promptly. I'm very happy with it and recommend it unreservedly.

- 4 very good for everyday wear or dressing up
- 5 The flute charm is so detailed and is of very high quality. You can see all the keys, any flute fan would adore having this item.
- 6 The message is very positive and it looks very pretty. I bought it for my aunt as a present and the color is very nice.
- 7 The diamond had a crack in one Garnet and another one had a large chip.
- 8 This medical alert braclet looked just like its picture and is nice quality sterling silver.

```
[45]: !pip install tabulate
      from tabulate import tabulate
      from summertime.evaluation import SUPPORTED EVALUATION METRICS
      from summertime.evaluation import BertScore, Meteor, Bleu
      import summertime.evaluation as st_eval
      print(SUPPORTED_EVALUATION_METRICS)
      targets = [
          'Gifted a ring to 16-year-old niece who loved and was happy to receive it.',
          'Ring is pretty, but the metal is insubstantial and can easily be pushed in.
       \hookrightarrow ,
          'High-quality item arrived quickly. Extremely satisfied and wholeheartedly_{\sqcup}
       ⇔recommend.',
          'Suitable and fashionable for dressy occasions.',
          'Received nice product earlier than expected. Will reorder.',
          'Colorful turtle items resembling the photograph. Comparable to expensive \sqcup
       ⇔ones, and beautiful.',
          'Ring appears smaller than pictured with very small diamonds, causingu
       ⇔disappointment.',
          'Medical alert bracelet matches picture and is made of quality sterling_{\sqcup}
       ⇔silver.',
      ]
      summaries = _values
      # Calculate BertScore
      bert_metric = BertScore()
      bert_results = bert_metric.evaluate(summaries, targets)
      # Calculate Meteor
      meteor_metric = Meteor()
      meteor_results = meteor_metric.evaluate(summaries, targets)
      # Calculate BLEU
      bleu metric = Bleu()
      bleu_results = bleu_metric.evaluate(summaries, targets)
```

```
# Print evaluation results
print(f"BertScore: {bert_results}")
print(f"Meteor: {meteor_results}")
print(f"BLEU: {bleu_results}")
# Print evaluation results in a table
table_data = [["BertScore", bert_results['bert_score_f1']],
               ["Meteor", meteor_results['meteor']],
               ["BLEU", bleu_results['bleu']]]
print(tabulate(table_data, headers=["Metric", "Score"], tablefmt="grid"))
Looking in indexes: https://pypi.org/simple, https://us-python.pkg.dev/colab-
wheels/public/simple/
Requirement already satisfied: tabulate in /usr/local/lib/python3.9/dist-
packages (0.8.10)
[<class 'summertime.evaluation.bertscore_metric.BertScore'>, <class
'summertime.evaluation.bleu_metric.Bleu'>, <class
'summertime.evaluation.rouge_metric.Rouge'>, <class
'summertime.evaluation.rougewe_metric.RougeWe'>, <class
'summertime.evaluation.meteor_metric.Meteor'>]
HBox(children=(FloatProgress(value=0.0, description='Downloading_
 →(...)okenizer_config.json', max=28.0, style=Pro...
HBox(children=(FloatProgress(value=0.0, description='Downloading (...)lve/main/
 ⇔config.json', max=570.0, style=Pr...
HBox(children=(FloatProgress(value=0.0, description='Downloading (...)solve/main/
 →vocab.txt', max=231508.0, style...
HBox(children=(FloatProgress(value=0.0, description='Downloading pytorch model.
 ⇔bin', max=440473133.0, style=Pr...
Some weights of the model checkpoint at bert-base-uncased were not used when
initializing BertModel: ['cls.predictions.transform.dense.weight',
'cls.predictions.decoder.weight', 'cls.predictions.transform.dense.bias',
'cls.predictions.bias', 'cls.predictions.transform.LayerNorm.weight',
'cls.seq_relationship.weight', 'cls.seq_relationship.bias',
'cls.predictions.transform.LayerNorm.bias']
- This IS expected if you are initializing BertModel from the checkpoint of a
model trained on another task or with another architecture (e.g. initializing a
BertForSequenceClassification model from a BertForPreTraining model).
```

```
- This IS NOT expected if you are initializing BertModel from the checkpoint of
a model that you expect to be exactly identical (initializing a
BertForSequenceClassification model from a BertForSequenceClassification model).
[nltk_data] Downloading package wordnet to /root/nltk_data...
            Package wordnet is already up-to-date!
[nltk data]
hash_code: bert-base-uncased_L8_no-idf_version=0.3.12(hug_trans=4.27.1)
BertScore: {'bert score f1': 0.5179015398025513}
Meteor: {'meteor': 0.11549545745316996}
BLEU: {'bleu': 0.03292378035323646}
+----+
| Metric
         Score |
+=======+
| BertScore | 0.517902 |
+----+
Meteor
         | 0.115495 |
+----+
         | 0.0329238 |
BLEU
+----+
Summarize evaluation anwer - TODO
```

#### 5b - Interactive summarization

```
[56]: no_sentences = input("Enter number of sentences you desire to be summarized")
      # list_val = list()
      user_summaries = list()
      summary_list = list()
      for i in range(0,int(no_sentences)):
       list_val = input(f"Enter sentence {i+1} \n")
       user_summaries.append(list_val)
       lexrank = model.LexRankModel(user_summaries)
        # # Inference
        summary = lexrank.summarize(user_summaries)
        summary_list.append(summary)
      for i, val in enumerate(user summaries):
        print(f"Summary for Sentence {i+1}")
       print(f"Summary {i+1} - {summary list[i]}")
        print('\n')
      # for key, corpus in enumerate(corpus_list):
      # print('\n' + f"QUERY \{key+1\} SUMMARIES")
        lexrank = model.LexRankModel(corpus)
      # # # Inference
      # summary = lexrank.summarize(corpus)
      # summary_list.append(summary)
         for i in range(len(summary)):
```

### # print("Summary Review %d: "%(i+1), summary[i])

Enter number of sentences you desire to be summarized2 Enter sentence 1

Arsenal was founded in 1886 as Dial Square, by workers at the Royal Arsenal in Woolwich. The club's first game was against Eastern Wanderers and ended in a 6-0 victory for Dial Square.

Enter sentence 2

Arsenal is one of the most successful clubs in English football history, having won 13 league titles, 14 FA Cups, and two European trophies. The club's most successful period came under the management of Arsene Wenger, who led the team to three Premier League titles and four FA Cups during his tenure from 1996 to 2018.

Summary for Sentence 1

Summary 1 - ["The club's first game was against Eastern Wanderers and ended in a 6-0 victory for Dial Square. Arsenal was founded in 1886 as Dial Square, by workers at the Royal Arsenal in Woolwich."]

Summary for Sentence 2

Summary 2 - ["The club's first game was against Eastern Wanderers and ended in a 6-0 victory for Dial Square. Arsenal was founded in 1886 as Dial Square, by workers at the Royal Arsenal in Woolwich.", "The club's most successful period came under the management of Arsene Wenger, who led the team to three Premier League titles and four FA Cups during his tenure from 1996 to 2018. Arsenal is one of the most successful clubs in English football history, having won 13 league titles, 14 FA Cups, and two European trophies."]

# []: sudo apt-get install texlive-xetex texlive-fonts-recommended\_ texlive-plain-generic

Reading package lists... Done
Building dependency tree

Reading state information... Done

The following additional packages will be installed:

dvisvgm fonts-droid-fallback fonts-lato fonts-lmodern fonts-noto-mono fonts-texgyre fonts-urw-base35 javascript-common libapache-pom-java libcommons-logging-java libcommons-parent-java libfontbox-java libgs9 libgs9-common libidn11 libijs-0.35 libjbig2dec0 libjs-jquery libkpathsea6 libpdfbox-java libptexenc1 libruby2.7 libsynctex2 libteckit0 libtexlua53 libtexluajit2 libzzip-0-13 lmodern poppler-data preview-latex-style rake ruby ruby-minitest ruby-net-telnet ruby-power-assert ruby-test-unit ruby-xmlrpc ruby2.7 rubygems-integration t1utils teckit tex-common tex-gyre texlive-base texlive-binaries texlive-latex-base texlive-latex-extra texlive-latex-recommended texlive-pictures tipa xfonts-encodings

# xfonts-utils Suggested packages: fonts-noto fonts-freefont-otf | fonts-freefont-ttf apache2 | lighttpd | httpd libavalon-framework-java libcommons-logging-java-doc libexcalibur-logkit-java liblog4j1.2-java poppler-utils ghostscript fonts-japanese-mincho | fonts-ipafont-mincho fonts-japanese-gothic | fonts-ipafont-gothic fonts-arphic-ukai fonts-arphic-uming fonts-nanum ri ruby-dev bundler debhelper gv | postscript-viewer perl-tk xpdf | pdf-viewer xzdec texlive-fonts-recommended-doc texlive-latex-base-doc python3-pygments icc-profiles libfile-which-perl libspreadsheet-parseexcel-perl texlive-latex-extra-doc texlive-latex-recommended-doc texlive-luatex texlive-pstricks dot2tex prerex ruby-tcltk | libtcltk-ruby texlive-pictures-doc vprerex The following NEW packages will be installed: dvisvgm fonts-droid-fallback fonts-lato fonts-lmodern fonts-noto-mono fonts-texgyre fonts-urw-base35 javascript-common libapache-pom-java libcommons-logging-java libcommons-parent-java libfontbox-java libgs9 libgs9-common libidn11 libijs-0.35 libjbig2dec0 libjs-jquery libkpathsea6 libpdfbox-java libptexenc1 libruby2.7 libsynctex2 libteckit0 libtexlua53 libtexluajit2 libzzip-0-13 lmodern poppler-data preview-latex-style rake ruby ruby-minitest ruby-net-telnet ruby-power-assert ruby-test-unit ruby-xmlrpc ruby2.7 rubygems-integration t1utils teckit tex-common tex-gyre texlive-base texlive-binaries texlive-fonts-recommended texlive-latex-base texlive-latex-extra texlive-latex-recommended texlive-pictures texlive-plain-generic texlive-xetex tipa xfonts-encodings xfonts-utils O upgraded, 55 newly installed, O to remove and 23 not upgraded. Need to get 169 MB of archives. After this operation, 536 MB of additional disk space will be used. Get:1 http://archive.ubuntu.com/ubuntu focal/main amd64 fonts-droid-fallback all 1:6.0.1r16-1.1 [1,805 kB] Get:2 http://archive.ubuntu.com/ubuntu focal/main amd64 fonts-lato all 2.0-2 [2,698 kB]Get:3 http://archive.ubuntu.com/ubuntu focal/main amd64 poppler-data all 0.4.9-2 [1,475 kB]Get:4 http://archive.ubuntu.com/ubuntu focal/universe amd64 tex-common all 6.13 [32.7 kB] Get:5 http://archive.ubuntu.com/ubuntu focal/main amd64 fonts-urw-base35 all 20170801.1-3 [6,333 kB] Get:6 http://archive.ubuntu.com/ubuntu focal-updates/main amd64 libgs9-common all 9.50~dfsg-5ubuntu4.6 [681 kB]

0.35-15 [15.7 kB]
Get:9 http://archive.ubuntu.com/ubuntu focal/main amd64 libjbig2dec0 amd64
0.18-1ubuntu1 [60.0 kB]

Get:8 http://archive.ubuntu.com/ubuntu focal/main amd64 libijs-0.35 amd64

Get:7 http://archive.ubuntu.com/ubuntu focal/main amd64 libidn11 amd64

1.33-2.2ubuntu2 [46.2 kB]

Get:10 http://archive.ubuntu.com/ubuntu focal-updates/main amd64 libgs9 amd64 9.50~dfsg-5ubuntu4.6 [2,173 kB]

```
Get:11 http://archive.ubuntu.com/ubuntu focal/main amd64 libkpathsea6 amd64 2019.20190605.51237-3build2 [57.0 kB]
```

Get:12 http://archive.ubuntu.com/ubuntu focal/universe amd64 dvisvgm amd64 2.8.1-1build1 [1,048 kB]

Get:13 http://archive.ubuntu.com/ubuntu focal/universe amd64 fonts-lmodern all 2.004.5-6 [4,532 kB]

Get:14 http://archive.ubuntu.com/ubuntu focal-updates/main amd64 fonts-noto-mono all 20200323-1build1~ubuntu20.04.1 [80.6 kB]

Get:15 http://archive.ubuntu.com/ubuntu focal/universe amd64 fonts-texgyre all 20180621-3 [10.2 MB]

Get:16 http://archive.ubuntu.com/ubuntu focal/main amd64 javascript-common all
11 [6,066 B]

Get:17 http://archive.ubuntu.com/ubuntu focal/universe amd64 libapache-pom-java all 18-1 [4,720 B]

Get:18 http://archive.ubuntu.com/ubuntu focal/universe amd64 libcommons-parent-java all 43-1 [10.8 kB]

Get:19 http://archive.ubuntu.com/ubuntu focal/universe amd64 libcommons-logging-java all 1.2-2 [60.3 kB]

Get:20 http://archive.ubuntu.com/ubuntu focal/main amd64 libjs-jquery all
3.3.1~dfsg-3 [329 kB]

Get:21 http://archive.ubuntu.com/ubuntu focal/main amd64 libptexenc1 amd64 2019.20190605.51237-3build2 [35.5 kB]

Get:22 http://archive.ubuntu.com/ubuntu focal/main amd64 rubygems-integration
all 1.16 [5,092 B]

Get:23 http://archive.ubuntu.com/ubuntu focal-updates/main amd64 ruby2.7 amd64 2.7.0-5ubuntu1.7 [95.6 kB]

Get:24 http://archive.ubuntu.com/ubuntu focal/main amd64 ruby amd64 1:2.7+1 [5,412 B]

Get:25 http://archive.ubuntu.com/ubuntu focal/main amd64 rake all 13.0.1-4 [61.6 kB]

Get:26 http://archive.ubuntu.com/ubuntu focal/main amd64 ruby-minitest all
5.13.0-1 [40.9 kB]

Get:27 http://archive.ubuntu.com/ubuntu focal/main amd64 ruby-net-telnet all 0.1.1-2 [12.6 kB]

Get:28 http://archive.ubuntu.com/ubuntu focal/main amd64 ruby-power-assert all 1.1.7-1 [11.4 kB]

Get:29 http://archive.ubuntu.com/ubuntu focal/main amd64 ruby-test-unit all
3.3.5-1 [73.2 kB]

Get:30 http://archive.ubuntu.com/ubuntu focal/main amd64 ruby-xmlrpc all 0.3.0-2 [23.8 kB]

Get:31 http://archive.ubuntu.com/ubuntu focal-updates/main amd64 libruby2.7 amd64 2.7.0-5ubuntu1.7 [3,533 kB]

Get:32 http://archive.ubuntu.com/ubuntu focal/main amd64 libsynctex2 amd64
2019.20190605.51237-3build2 [55.0 kB]

Get:33 http://archive.ubuntu.com/ubuntu focal/universe amd64 libteckit0 amd64
2.5.8+ds2-5ubuntu2 [320 kB]

Get:34 http://archive.ubuntu.com/ubuntu focal/main amd64 libtexlua53 amd64 2019.20190605.51237-3build2 [105 kB]

```
Get:35 http://archive.ubuntu.com/ubuntu focal/main amd64 libtexluajit2 amd64
2019.20190605.51237-3build2 [235 kB]
Get:36 http://archive.ubuntu.com/ubuntu focal/universe amd64 libzzip-0-13 amd64
0.13.62-3.2ubuntu1 [26.2 kB]
Get:37 http://archive.ubuntu.com/ubuntu focal/main amd64 xfonts-encodings all
1:1.0.5-0ubuntu1 [573 kB]
Get:38 http://archive.ubuntu.com/ubuntu focal/main amd64 xfonts-utils amd64
1:7.7+6 [91.5 kB]
Get:39 http://archive.ubuntu.com/ubuntu focal/universe amd64 lmodern all
2.004.5-6 [9,474 kB]
Get:40 http://archive.ubuntu.com/ubuntu focal/universe amd64 preview-latex-style
all 11.91-2ubuntu2 [184 kB]
Get:41 http://archive.ubuntu.com/ubuntu focal/main amd64 t1utils amd64 1.41-3
[56.1 kB]
Get:42 http://archive.ubuntu.com/ubuntu focal/universe amd64 teckit amd64
2.5.8+ds2-5ubuntu2 [687 kB]
Get:43 http://archive.ubuntu.com/ubuntu focal/universe amd64 tex-gyre all
20180621-3 [6,209 kB]
Get:44 http://archive.ubuntu.com/ubuntu focal/universe amd64 texlive-binaries
amd64 2019.20190605.51237-3build2 [8,041 kB]
Get:45 http://archive.ubuntu.com/ubuntu focal/universe amd64 texlive-base all
2019.20200218-1 [20.8 MB]
Get:46 http://archive.ubuntu.com/ubuntu focal/universe amd64 texlive-fonts-
recommended all 2019.20200218-1 [4,972 kB]
Get:47 http://archive.ubuntu.com/ubuntu focal/universe amd64 texlive-latex-base
all 2019.20200218-1 [990 kB]
Get:48 http://archive.ubuntu.com/ubuntu focal/universe amd64 libfontbox-java all
1:1.8.16-2 [207 kB]
Get:49 http://archive.ubuntu.com/ubuntu focal/universe amd64 libpdfbox-java all
1:1.8.16-2 [5,199 kB]
Get:50 http://archive.ubuntu.com/ubuntu focal/universe amd64 texlive-latex-
recommended all 2019.20200218-1 [15.7 MB]
Get:51 http://archive.ubuntu.com/ubuntu focal/universe amd64 texlive-pictures
```

all 2019.20200218-1 [4,492 kB]

Get:52 http://archive.ubuntu.com/ubuntu focal/universe amd64 texlive-latex-extra all 2019.202000218-1 [12.5 MB]

Get:53 http://archive.ubuntu.com/ubuntu focal/universe amd64 texlive-plaingeneric all 2019.202000218-1 [24.6 MB]

82% [53 texlive-plain-generic 6,852 kB/24.6 MB 28%]

4,961 kB/s 7s

## [1]: # %%shell

!jupyter nbconvert --to pdf '/content/drive/My Drive/Colab Notebooks/COP509cw/ →NLPCoursework.ipynb'

[NbConvertApp] Converting notebook /content/drive/My Drive/Colab Notebooks/COP509cw/NLPCoursework.ipynb to pdf /usr/local/lib/python3.9/dist-packages/nbconvert/filters/datatypefilter.py:41:

```
UserWarning: Your element with mimetype(s) dict keys(['text/html']) is not able
to be represented.
  warn(
[NbConvertApp] Support files will be in NLPCoursework_files/
[NbConvertApp] Making directory ./NLPCoursework files
[NbConvertApp] Making directory ./NLPCoursework_files
[NbConvertApp] Making directory ./NLPCoursework files
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[NbConvertApp] Making directory ./NLPCoursework_files
[NbConvertApp] Writing 380052 bytes to notebook.tex
[NbConvertApp] Building PDF
Traceback (most recent call last):
  File "/usr/local/bin/jupyter-nbconvert", line 8, in <module>
    sys.exit(main())
 File "/usr/local/lib/python3.9/dist-packages/jupyter_core/application.py",
line 277, in launch_instance
    return super().launch_instance(argv=argv, **kwargs)
 File "/usr/local/lib/python3.9/dist-packages/traitlets/config/application.py",
line 992, in launch instance
   app.start()
 File "/usr/local/lib/python3.9/dist-packages/nbconvert/nbconvertapp.py", line
423, in start
    self.convert_notebooks()
 File "/usr/local/lib/python3.9/dist-packages/nbconvert/nbconvertapp.py", line
597, in convert_notebooks
    self.convert_single_notebook(notebook_filename)
 File "/usr/local/lib/python3.9/dist-packages/nbconvert/nbconvertapp.py", line
560, in convert_single_notebook
   output, resources = self.export_single_notebook(
  File "/usr/local/lib/python3.9/dist-packages/nbconvert/nbconvertapp.py", line
488, in export_single_notebook
```

```
output, resources = self.exporter.from_filename(
 File "/usr/local/lib/python3.9/dist-packages/nbconvert/exporters/exporter.py",
line 189, in from_filename
   return self.from_file(f, resources=resources, **kw)
 File "/usr/local/lib/python3.9/dist-packages/nbconvert/exporters/exporter.py",
line 206, in from_file
   return self.from notebook node(
 File "/usr/local/lib/python3.9/dist-packages/nbconvert/exporters/pdf.py", line
194, in from_notebook_node
   self.run_latex(tex_file)
 File "/usr/local/lib/python3.9/dist-packages/nbconvert/exporters/pdf.py", line
164, in run_latex
   return self.run_command(
 File "/usr/local/lib/python3.9/dist-packages/nbconvert/exporters/pdf.py", line
111, in run_command
   raise OSError(
OSError: xelatex not found on PATH, if you have not installed xelatex you may
need to do so. Find further instructions at
https://nbconvert.readthedocs.io/en/latest/install.html#installing-tex.
```

[]: