F218341_NLPCoursework

March 24, 2023

#Mount Drive

[1]:
```
from google.colab import drive
drive.mount("/content/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.csv                JewelleryReviewsQueryRelevantID.gsheet
JewelleryReviewsLSA.gsheet             JewelleryReviewsSummarisationTargets.csv
JewelleryReviewsQueryRelevantID.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]    |
[nltk_data]    | Downloading package cmudict to /root/nltk_data…
[nltk_data]    |   Package cmudict is already up-to-date!
[nltk_data]    | Downloading package gazetteers to /root/nltk_data…
[nltk_data]    |   Package gazetteers is already up-to-date!
[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]    |   Package movie_reviews is already up-to-date!
[nltk_data]    | Downloading package names to /root/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!
[nltk_data]    | Downloading package stopwords to /root/nltk_data…
[nltk_data]    |   Package stopwords is already up-to-date!
[nltk_data]    | Downloading package treebank to /root/nltk_data…
[nltk_data]    |   Package treebank is already up-to-date!
[nltk_data]    | Downloading package twitter_samples to
[nltk_data]    |     /root/nltk_data…
[nltk_data]    |   Package twitter_samples is already up-to-date!
[nltk_data]    | Downloading package omw to /root/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!
[nltk_data]    | Downloading package wordnet2021 to /root/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!
[nltk_data]    | Downloading package wordnet_ic to /root/nltk_data…
[nltk_data]    |   Package wordnet_ic is already up-to-date!
[nltk_data]    | Downloading package words to /root/nltk_data…
[nltk_data]    |   Package words is already up-to-date!
[nltk_data]    | Downloading package maxent_ne_chunker to
[nltk_data]    |     /root/nltk_data…
[nltk_data]    |   Package maxent_ne_chunker is already up-to-date!
[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]    |     /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…
[nltk_data]    |   Package averaged_perceptron_tagger is already up-
[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/
↪1dTFUKVnqCJVuQckf0kbfaFNb8kK7bX5y?usp=sharing#scrollTo=NKc7lfr6D-ts]
```

```python
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), ('one', 32), ('look', 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), ('seller',
10), ('wedding', 10), ('diamonds', 10), ('right', 10), ('purchased', 10),
('wanted', 10), ('wearing', 10), ('much', 10), ('order', 10), ('stones', 10)]
450
```

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_CppdfOSk
def prepare_data(train_docs, mode, vocab):
        # encode training data set
        vectorizer = CountVectorizer(vocabulary=vocab)
        transformer = TfidfTransformer(norm='l2')
        Xtrain = transformer.fit_transform(vectorizer.fit_transform(train_docs))
        return Xtrain

# # This code block was copied from - https://colab.research.google.com/drive/
↪1gonQXIxPTDk7WUsbDQ2G7neURoWP6efH#scrollTo=HFeOO9Ca-BX-&line=12&uniqifier=1
# preprocess query
```

```python
def preprocess_query(query, mode, vocab):
  line = doc_to_line(query, vocab)
  vectorizer = CountVectorizer(vocabulary=vocab)
  transformer = TfidfTransformer(norm='l2')
  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]:

```python
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␣
 ↪not very noticeable',
          'braclet looked just like its picture and is nice quality sterling␣
 ↪silver.'
]



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)
```

```
print(f"Top {Top_n_reviews} documents retrieved:  {str(doc_id)}")
# print(f"Top {Top_n_reviews} documents retrieved:  {data.
↪iloc[indexes]["ID"]}")
similarity_score = ', '.join([str(round(score, 3)) for score in similarities.
                              flat[indexes]])
print(f"\nSimilarities scores: {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('\n')
```

```
--------------------------------------------------------------------------------
--------------------
Query 1: The ring is a great gift. My friend loves it
================================================================================
====================
Top 10 documents retrieved:  [58595, 26246, 2033, 35694, 17273, 41876, 17309,
44591, 36164, 49525]

Similarities scores: 0.952, 0.953, 0.964, 0.973, 0.974, 0.976, 0.977, 0.98,
0.988, 0.996
================================================================================
====================
10th Ranked result:
Doc ID: 51
I absolutely love this ring! I got this as my engagement ring Feb 09 This ring
is beautiful and durable.
Similarities: 0.9516066884975152


9th 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: 0.9525073901834404


8th 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: 0.9637988775985414

7th 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: 0.9733570704095903

6th 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: 0.9739711458734214

5th 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: 0.9759727124396379

4th 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: 0.9765636162003816

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: 0.980235135588057

2th Ranked result:
Doc ID: 103
I got the ring as a promise ring for my girlfriend for Christmas and she loved it. Definitely a great value.
Similarities: 0.9882383005573151

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: 0.996196988744203


--------------------------------------------------------------------------------
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Query 2: horrible bad quality bracelet
================================================================================
====================
Top 10 documents retrieved:  [10758, 1816, 265, 17944, 13373, 2114, 33571,
54748, 45548, 38305]

Similarities scores: 0.97, 0.972, 0.973, 0.973, 0.977, 0.978, 0.981, 0.989,
0.99, 0.99
================================================================================
====================
10th Ranked result:
Doc ID: 96
Very impressed with the quality of my item. Delivery was fast. Would definately
buy from this seller again
Similarities: 0.970042933274013


9th Ranked result:
Doc ID: 5
The quality and look were not what I had anticipated. Very flimsy.I would not
recommend this item
Similarities: 0.9716911128853916


8th 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: 0.9727585456571965


7th Ranked result:
Doc ID: 134
the product i recieved was nice it came in a timley matter faster than i
expected will order this item again
Similarities: 0.9733617902352402


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: 0.9771525645983202


5th 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: 0.9775153326796236


4th 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: 0.98109050390739


3th 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: 0.9885902766592719


2th 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: 0.9897455010803554


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: 0.9901293986860161


--------------------------------------------------------------------------------
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Query 3: arrived promptly and happy with the seller
================================================================================
====================
```

```
Top 10 documents retrieved:  [6158, 27679, 10758, 4375, 32674, 49216, 41889,
29722, 22058, 33251]

Similarities scores: 0.96, 0.96, 0.963, 0.963, 0.963, 0.964, 0.97, 0.973, 0.991,
0.993
================================================================================
====================
10th Ranked result:
Doc ID: 129
Wonderful shopping experience I purchased the item for holiday presents and the
whole order came quickly and in wonderful condition.
Similarities: 0.9601008591282173


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 t
Similarities: 0.960288213754901


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: 0.9627720093494982


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: 0.9627720093494982


6th Ranked result:
Doc ID: 94
THIS ITEM WAS A WONDERFUL SURPRISE. THE QUALITY IS SO MUCH MORE THAN I COULD
HAVE EVER HOPED FOR.
Similarities: 0.9630478307992903


5th 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: 0.9637425292030909
```

```
4th 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: 0.9703923475029783


3th 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: 0.9726944562108203


2th Ranked result:
Doc ID: 100
Item was great quality and came promptly. I'm very happy with it and recommend
it unreservedly.
Similarities: 0.9910088534477722


1th 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: 0.9927408296300624



--------------------------------------------------------------------------------
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Query 4: wear it with casual wear
================================================================================
====================
Top 10 documents retrieved:  [12483, 2131, 11087, 44126, 37486, 28648, 2134,
535, 19852, 36585]

Similarities scores: 0.962, 0.972, 0.973, 0.974, 0.984, 0.985, 0.986, 0.989,
0.99, 0.997
================================================================================
====================
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: 0.9620973302662069


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: 0.9718907706235212


8th 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: 0.9728354085999258


7th 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: 0.9735536269516046


6th 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: 0.9840779871926518


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: 0.9853534881808587


4th Ranked result:
Doc ID: 145
ery suitable for wearing for fashionable occasions. very dressy
Similarities: 0.9859708694089536


3th Ranked result:
Doc ID: 14
It serves the purpose, but it seemed to me that the image was a lot prettier and
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sparklier than it turned out to be. I wear it UNDER my shirt since it does not
compliment anything I wear.
Similarities: 0.9885212612264651


2th Ranked result:
Doc ID: 144
very good for everyday wear or dressing up
Similarities: 0.9895013105178985


1th 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: 0.996904464759674



--------------------------------------------------------------------------------
--------------------
Query 5: i expected better quality. i will return this item
================================================================================
====================
Top 10 documents retrieved:  [1816, 265, 33571, 8110, 4375, 10758, 45548, 13373,
54748, 38305]

Similarities scores: 0.986, 0.987, 0.99, 0.991, 0.992, 0.992, 0.992, 0.994,
0.995, 0.998
================================================================================
====================
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: 0.9859778533466629


9th 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: 0.9866988263199411


8th 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: 0.9902471613429228


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: 0.991360616569033


6th Ranked result:
Doc ID: 95
Very impressed with the quality of my item. Delivery was fast. Would definately
buy from this seller again
Similarities: 0.991983279826615


5th Ranked result:
Doc ID: 96
Very impressed with the quality of my item. Delivery was fast. Would definately
buy from this seller again
Similarities: 0.991983279826615


4th 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: 0.9923578187050457


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: 0.9935108665229541


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: 0.9949888773878042


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: 0.9976885317331038


--------------------------------------------------------------------------------
--------------------
Query 6: looks beautiful. The design is pretty. pefect and color is light
================================================================================
====================
Top 10 documents retrieved:  [27474, 12358, 32767, 52375, 28543, 42077, 46500,
41319, 39932, 45860]

Similarities scores: 0.912, 0.915, 0.924, 0.929, 0.944, 0.948, 0.953, 0.97,
0.971, 0.974
================================================================================
====================
10th 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: 0.9116660871926511


9th 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: 0.9145509765736337


8th 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: 0.9242536403779749


7th Ranked result:
Doc ID: 169
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.
Similarities: 0.9291564105255532
```

6th Ranked result:
Doc ID: 192
The diamond had a crack in one Garnet and another one had a large chip.
Similarities: 0.944046009230834

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: 0.9482139592367441

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: 0.9525993103279228

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: 0.9699250438487333

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: 0.9710103319635547

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: 0.9739226900713983

```
Query 7: This ring looks nothing like the picture. the diamonds are small and
not very noticeable
================================================================================
====================
Top 10 documents retrieved:  [3494, 11356, 6649, 37864, 28542, 38637, 47345,
943, 41872, 209]

Similarities scores: 0.958, 0.963, 0.97, 0.971, 0.973, 0.976, 0.981, 0.989,
0.991, 0.992
================================================================================
====================
10th Ranked result:
Doc ID: 188
It is as nice as it looks on the picture. :) I like it. :)
Similarities: 0.9575701312339923


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: 0.9633444455948056


8th 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: 0.9701539312132591


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: 0.9709707315626354


6th 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: 0.9733061542925641
```

```
5th 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: 0.9759518827004349


4th 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: 0.9812440106314239


3th 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: 0.9890072026188487


2th 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: 0.9912366909523781


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: 0.9919792196944744


--------------------------------------------------------------------------------
--------------------
Query 8: braclet looked just like its picture and is nice quality sterling
silver.
================================================================================
====================
Top 10 documents retrieved:  [47345, 735, 41872, 10642, 3494, 53409, 44490,
```

```
45518, 56865, 642]

Similarities scores: 0.927, 0.929, 0.934, 0.94, 0.95, 0.969, 0.978, 0.988,
0.992, 1.0
================================================================================
====================
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: 0.9267682557723776


9th 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: 0.9294737921174739


8th 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: 0.9335894845918463


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: 0.9396554600244953


6th Ranked result:
Doc ID: 188
It is as nice as it looks on the picture. :) I like it. :)
Similarities: 0.9496090385591522


5th Ranked result:
Doc ID: 193
Although the picture looks like metal beads and description states sterling
silver, these are pearls.
Similarities: 0.9686431063452202
```

```
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: 0.9783791007342493


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: 0.988441239575514


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: 0.9921682442597244


1th Ranked result:
Doc ID: 184
This medical alert braclet looked just like its picture and is nice quality
sterling silver.
Similarities: 0.9995148774539916
```

2.2 2b - Emperically Tune the LSI model

Define functions for Emperical tuning of Weighting schemes

[8]:
```
from sklearn.feature_extraction.text import TfidfVectorizer
import matplotlib.pyplot as plt

def prepare_tf_data(train_docs, mode, vocab):
  # encode training data set
        vectorizer = CountVectorizer(vocabulary=vocab)
        transformer = TfidfTransformer(norm=None, use_idf=False,␣
 ↪sublinear_tf=True)
        Xtrain = transformer.fit_transform(vectorizer.fit_transform(train_docs))
        return Xtrain

def preprocess_tf_query(query, mode, vocab):
  line = doc_to_line(query, vocab)
  vectorizer = CountVectorizer(vocabulary=vocab)
```

```
  transformer = TfidfTransformer(norm=None, use_idf=False, sublinear_tf=True)
  encoded = transformer.fit_transform(vectorizer.fit_transform([line]))
  return encoded

# 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_CppdfOSk
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/
↪1gonQXIxPTDk7WUsbDQ2G7neURoWP6efH#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))
```

Define Evaluation Metrics

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

```python
    if p >= 1.0:
        p = 0.9

    Mark = np.zeros(2)
    l = 0
    r = 0
    for i in range(len(Recall)):
        if Recall[i] >= p and Mark[0] == 0:
            l = 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[l:(r+1)])
    return y

# obtain y axis for R/P curve
def compute_RP_yaxis(Precision=None, Recall=None):
  y_axis = [1.0, 1.0, 1.0, 1.0, 1.0, 1.0, 1.0, 1.0, 1.0, 1.0, 1.0]
  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*

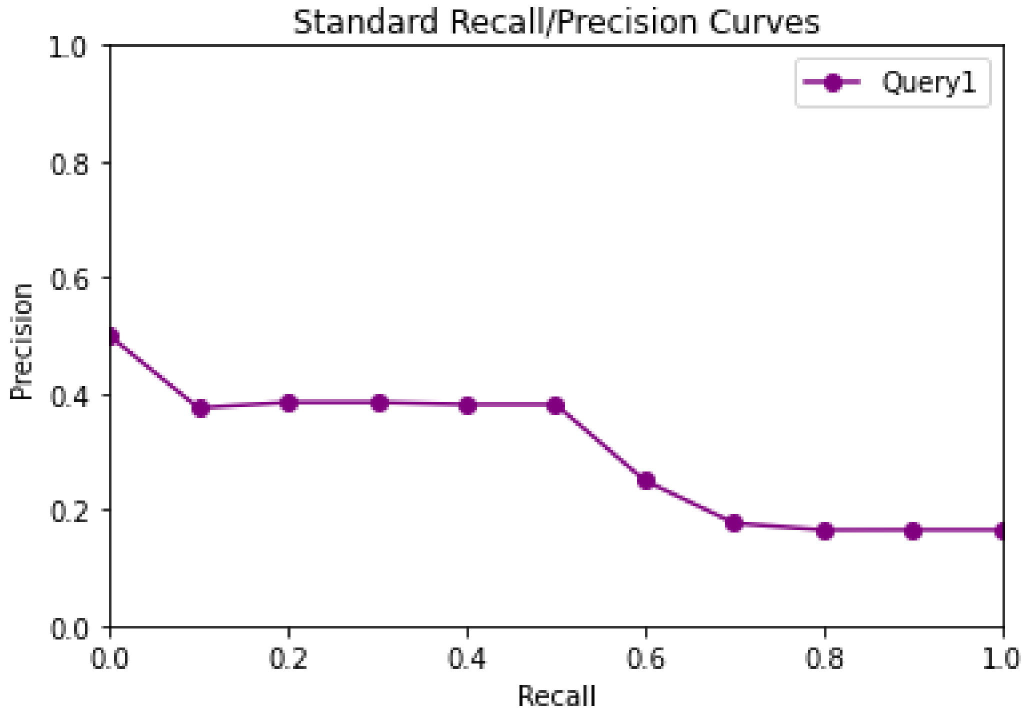
[10]:
```
Xtrain = _prepare_data(reviews, 'tf', vocab)
trunc_SVD_model = TruncatedSVD(n_components=5)
approx_Xtrain = trunc_SVD_model.fit_transform(Xtrain)

re_ID =␣
 ↪[[36164,58481,26246,2033,48779,34523,9726,56494,49525,45278,35694,41876,17309,11135,17273,1
          [57123,25299,55017,7432,2114,40871],
          ␣
 ↪[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 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()

LSI_y_axis_avg = y_axis
```

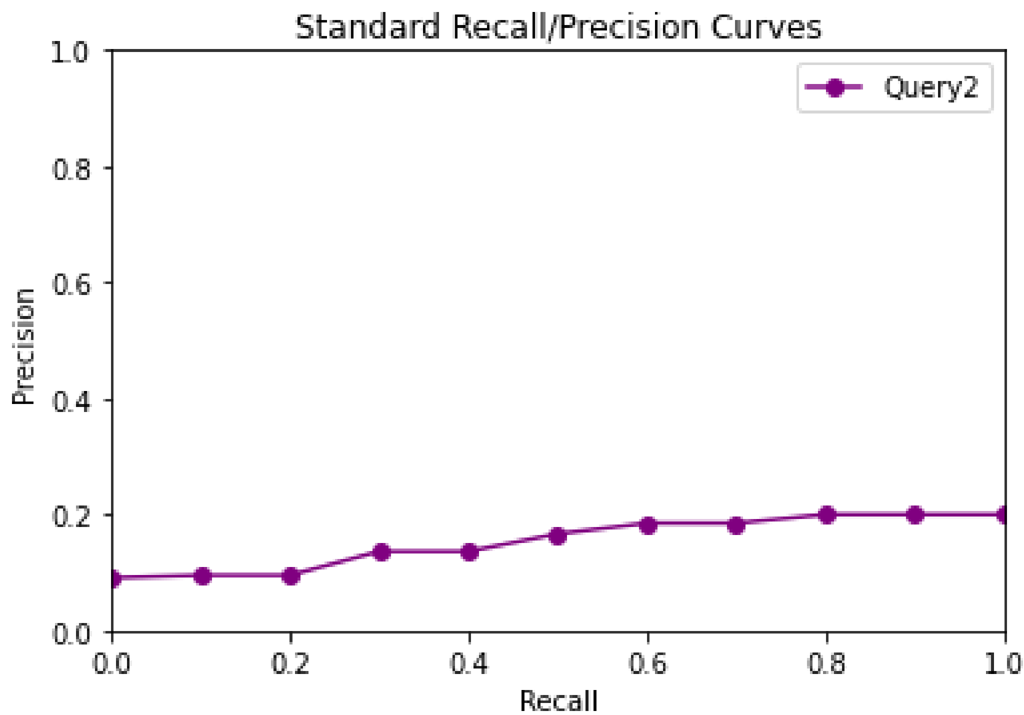
```
Query1: The ring is a great gift. My friend loves it
Recall@1~10:  [0.   0.06 0.06 0.06 0.06 0.06 0.12 0.19 0.19 0.19]
Precision@1~10:  [0.   0.5  0.33 0.25 0.2  0.17 0.29 0.38 0.33 0.3 ]
F1measure@1~10:  [0.   0.11 0.11 0.1  0.1  0.09 0.17 0.25 0.24 0.23]
```

```
<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.
  plt.plot(x_axis, y_axis, '-bo', color="purple", label="Query%d"%(j+1))
```



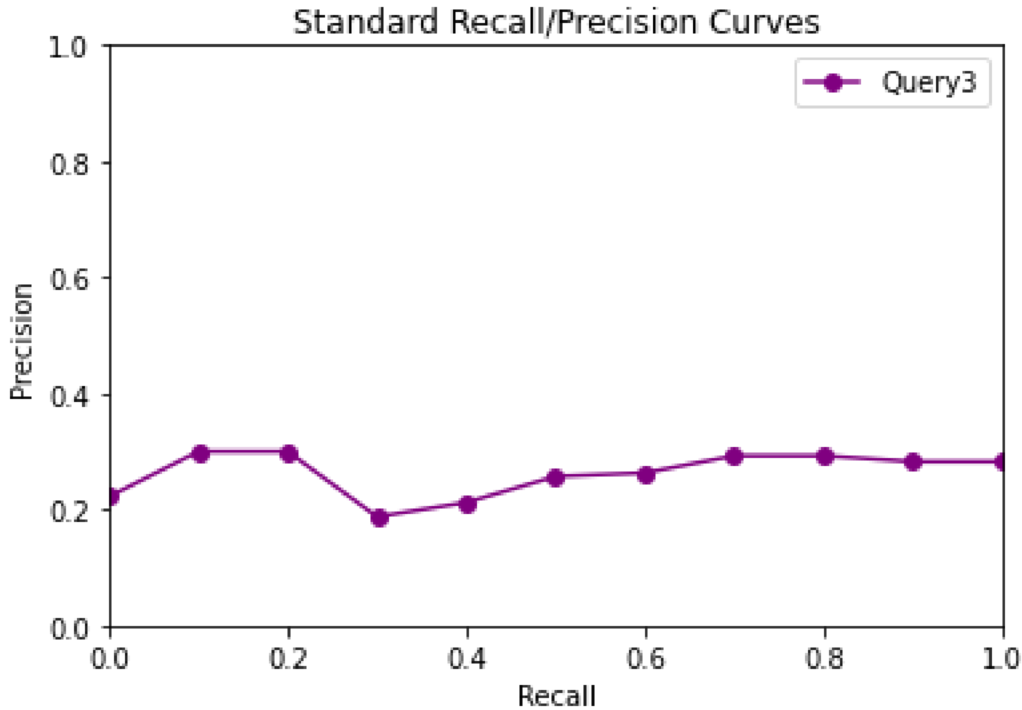

```
Query2: horrible bad quality bracelet
Recall@1~10:  [0. 0. 0. 0. 0. 0. 0. 0. 0. 0.]
Precision@1~10:  [0. 0. 0. 0. 0. 0. 0. 0. 0. 0.]
F1measure@1~10:  [0. 0. 0. 0. 0. 0. 0. 0. 0. 0.]
```

```
<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.
  plt.plot(x_axis, y_axis, '-bo', color="purple", label="Query%d"%(j+1))
```



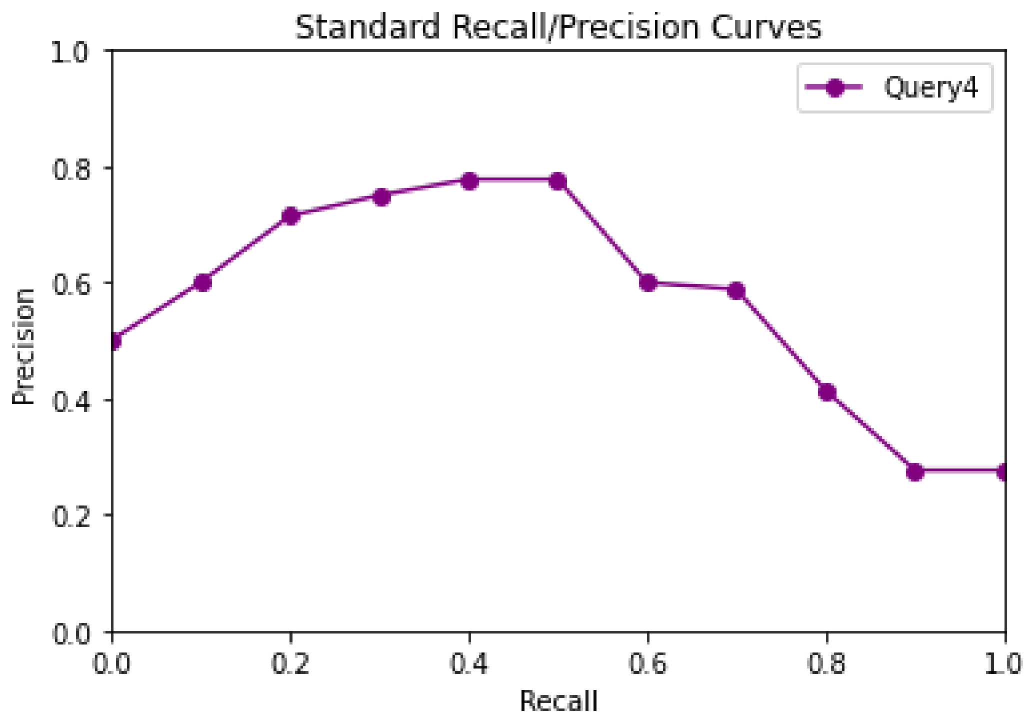

```
Query3: arrived promptly and happy with the seller
Recall@1~10:  [0.   0.   0.   0.   0.   0.07 0.07 0.07 0.14 0.21]
Precision@1~10:  [0.   0.   0.   0.   0.   0.17 0.14 0.12 0.22 0.3 ]
F1measure@1~10:  [0.   0.   0.   0.   0.   0.1  0.1  0.09 0.17 0.25]
```

```
<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))
```




```
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]
```

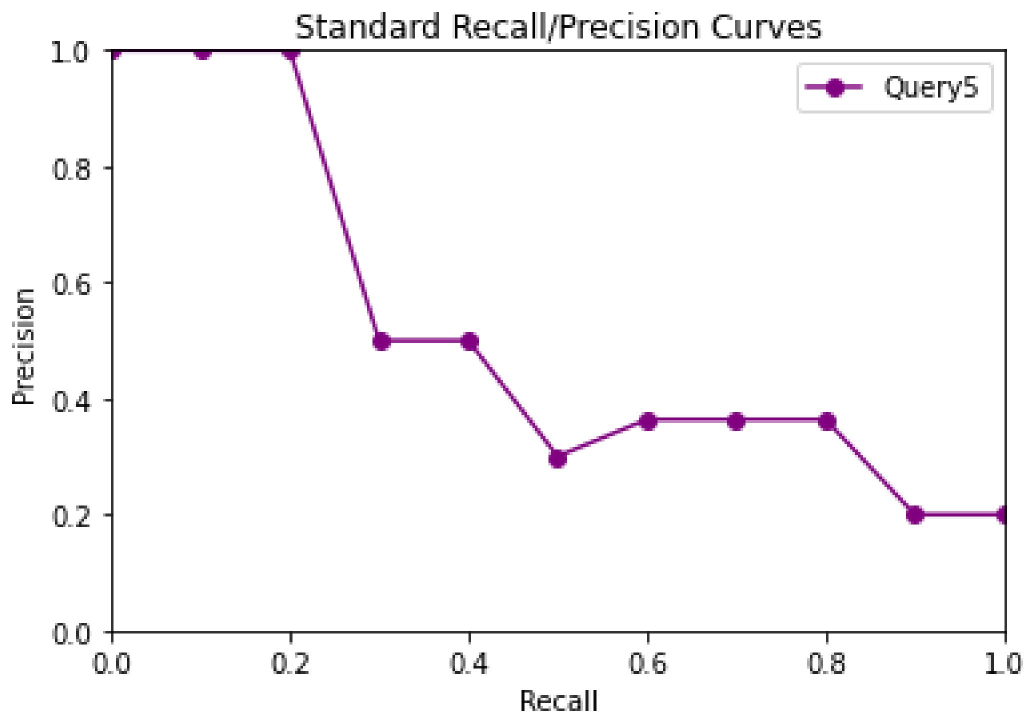
```
<ipython-input-10-1e3085a49a4c>:64: UserWarning: color is redundantly defined by
the 'color' keyword argument and the fmt string "-bo" (-> color='b'). The
keyword argument will take precedence.
  plt.plot(x_axis, y_axis, '-bo', color="purple", label="Query%d"%(j+1))
```




```
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 0.4 0.6]
```

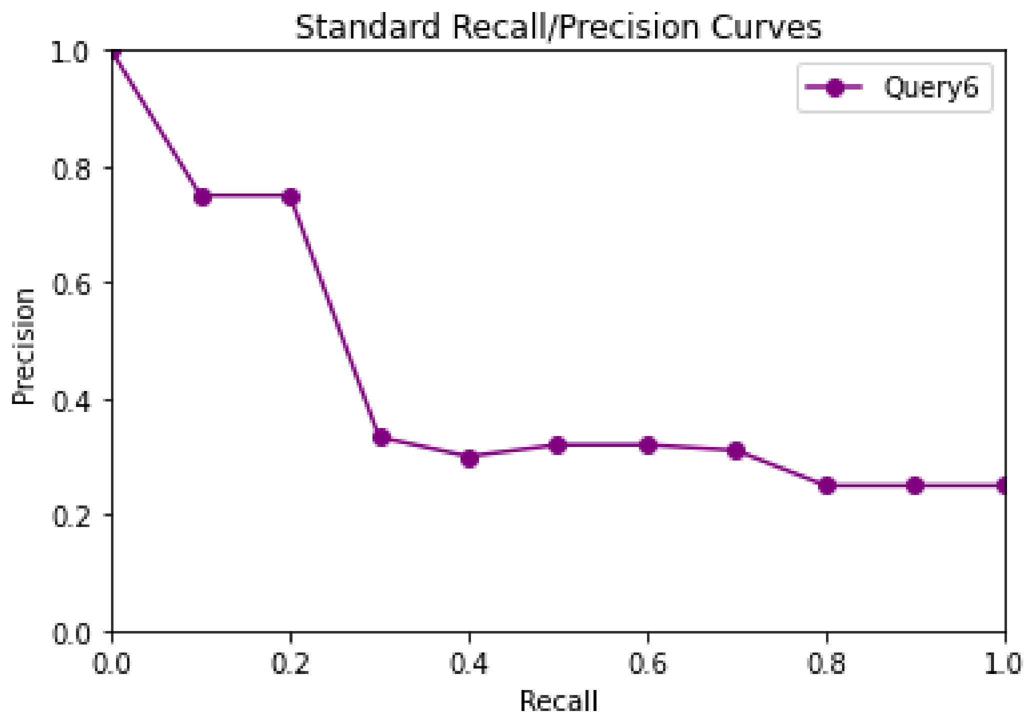
```
<ipython-input-10-1e3085a49a4c>:64: UserWarning: color is redundantly defined by
the 'color' keyword argument and the fmt string "-bo" (-> color='b'). The
keyword argument will take precedence.
  plt.plot(x_axis, y_axis, '-bo', color="purple", label="Query%d"%(j+1))
```

```
Precision@1~10:  [1.   0.5  0.33 0.5  0.4  0.33 0.29 0.25 0.22 0.3 ]
F1measure@1~10:  [0.33 0.29 0.25 0.44 0.4  0.36 0.33 0.31 0.29 0.4 ]
```



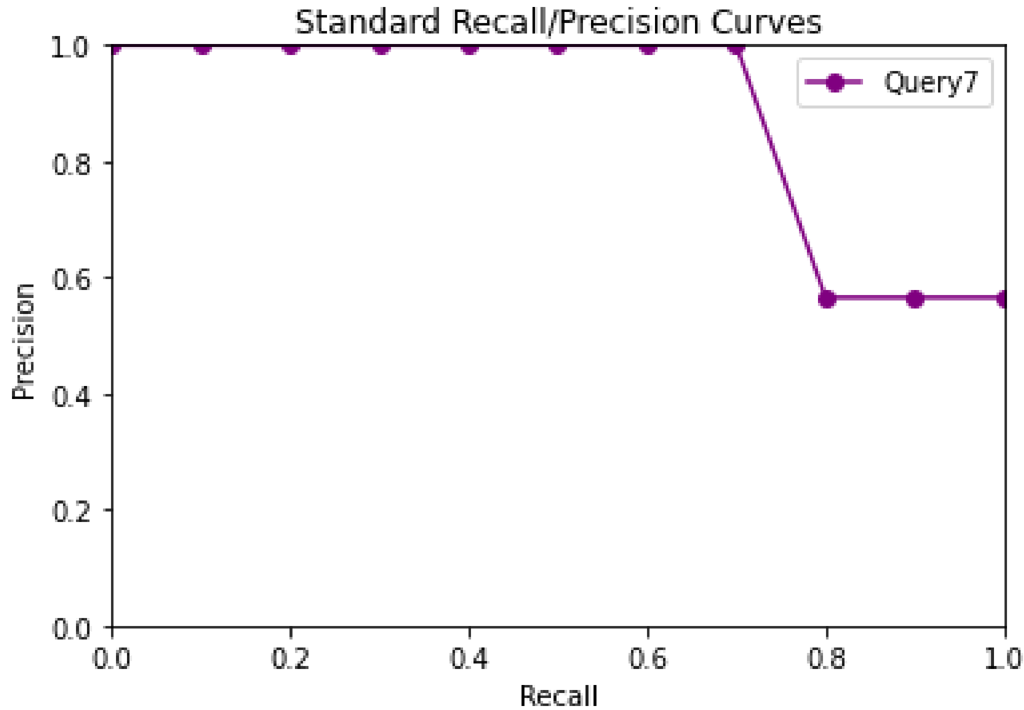

```
Query6: looks beautiful. The design is pretty. pefect and color is light
Recall@1~10:  [0.08 0.08 0.17 0.25 0.25 0.25 0.25 0.25 0.25 0.25]
Precision@1~10:  [1.   0.5  0.67 0.75 0.6  0.5  0.43 0.38 0.33 0.3 ]
F1measure@1~10:  [0.15 0.14 0.27 0.38 0.35 0.33 0.32 0.3  0.29 0.27]
```

```
<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))
```



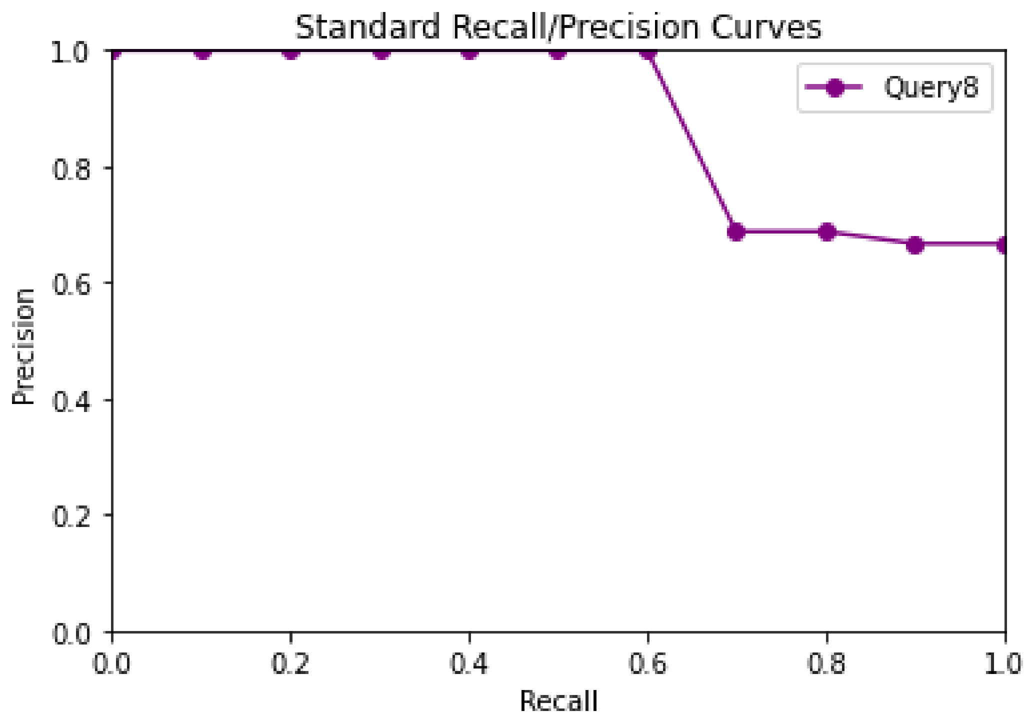

```
Query7: This ring looks nothing like the picture. the diamonds are small and not
very noticeable
Recall@1~10:  [0.07 0.14 0.21 0.29 0.36 0.43 0.5  0.57 0.64 0.71]
Precision@1~10:  [1. 1. 1. 1. 1. 1. 1. 1. 1. 1.]
F1measure@1~10:  [0.13 0.25 0.35 0.44 0.53 0.6  0.67 0.73 0.78 0.83]
```

```
<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.
  plt.plot(x_axis, y_axis, '-bo', color="purple", label="Query%d"%(j+1))
```



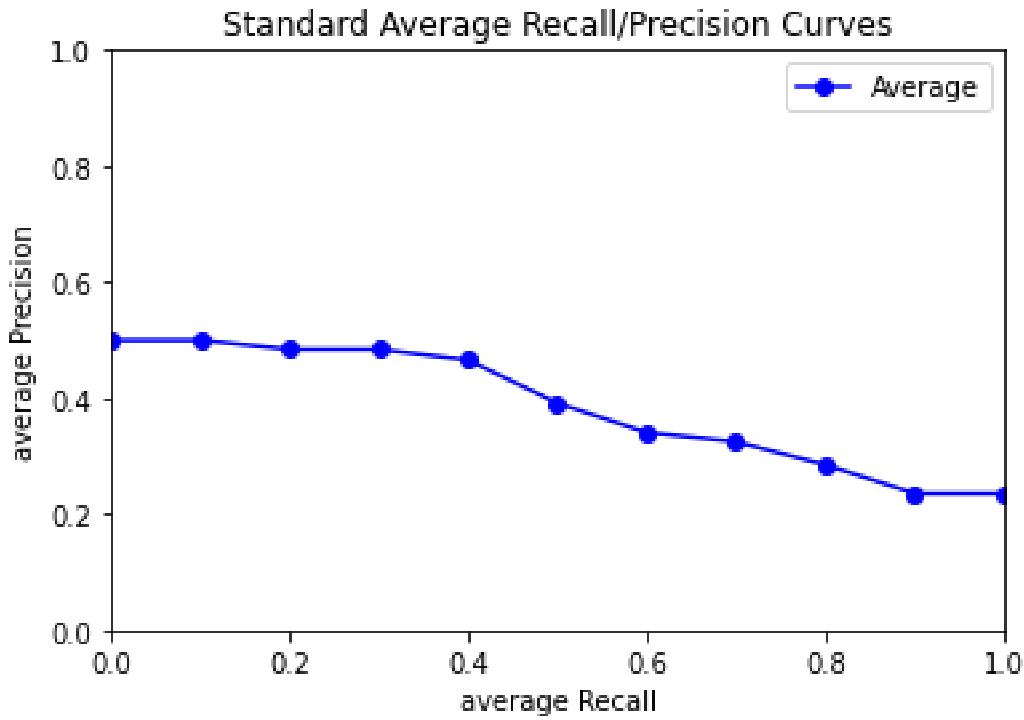

```
Query8: braclet looked just like its picture and is nice quality sterling
silver.
Recall@1~10:  [0.08 0.15 0.23 0.31 0.38 0.46 0.54 0.62 0.62 0.62]
Precision@1~10:  [1.   1.   1.   1.   1.   1.   1.   1.   0.89 0.8 ]
F1measure@1~10:  [0.14 0.27 0.38 0.47 0.56 0.63 0.7  0.76 0.73 0.7 ]
```

```
<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))
```




```
Average Recall, average Precision, average F1-measure:
average Recall@1~10:  [0.05 0.09 0.12 0.18 0.21 0.24 0.28 0.32 0.34 0.39]
average Precision@1~10:  [0.5  0.5  0.46 0.5  0.48 0.48 0.48 0.48 0.47 0.46]
average F1measure@1~10:  [0.1  0.15 0.18 0.26 0.28 0.31 0.35 0.37 0.39 0.41]
```

```
<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'], row['Precision'],␣
↪row['F1measure']])
  print(pt)

  # Plot table
def plot_avg_table(result):
  pt = PrettyTable()
```

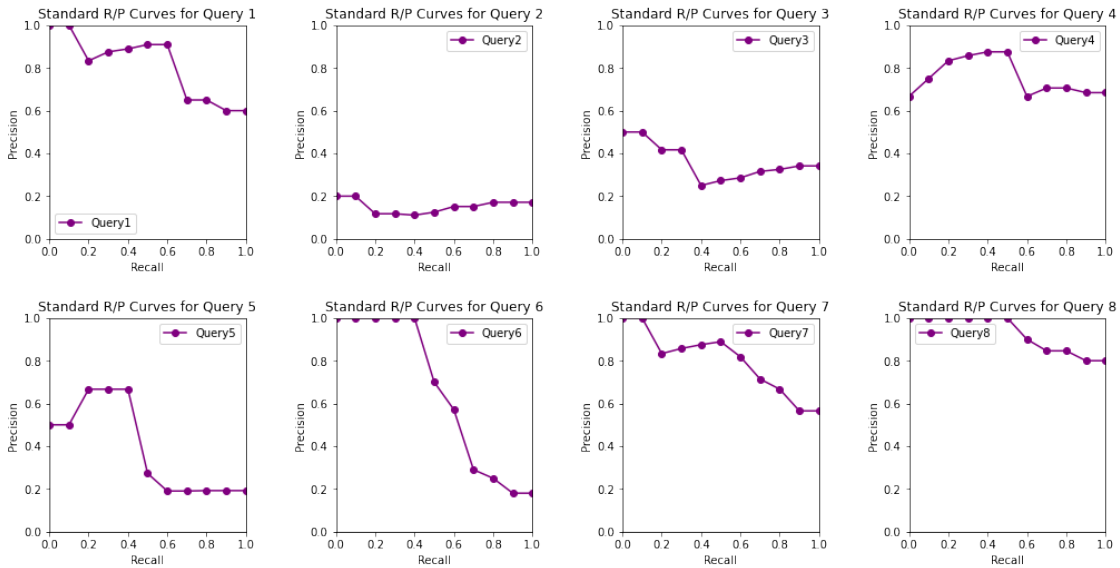
```
  # Add columns to the PrettyTable
  pt.field_names = ['Query', 'Average Recall', 'Average Precision', 'Average␣
 ↪F1measure']

  # Add rows from results to the table
  for index, row in result.iterrows():
    pt.add_row([index+1, row['Average Recall'], row['Average Precision'],␣
 ↪row['Average F1measure']])
  print(pt)

# Define tuning parameters for weighthing schemes and SVD parameters
Xtrain = _prepare_data(reviews, 'tfidf', 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],
        ␣
 ↪[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()

# 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', 'Recall', 'Precision', 'F1measure'])

# loop queries
```

```python
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
```

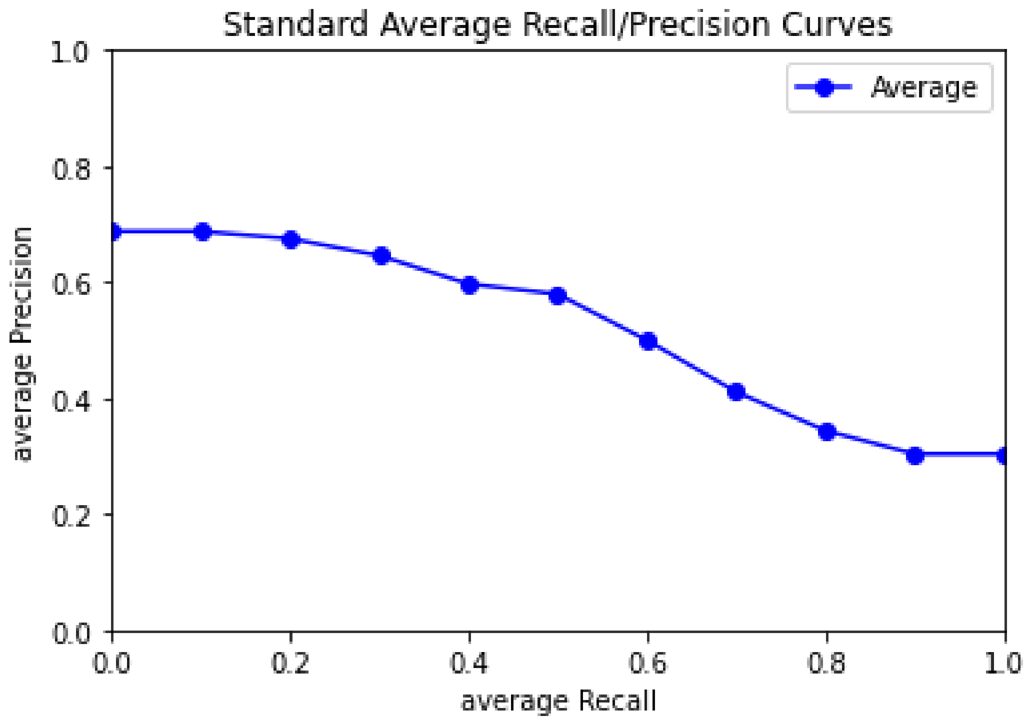
```
print("\nResults for top n docs returned for each query:")
plot_df_table(results_df)

# 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': np.around(AveRecall[10:], 2),
                                'Average Precision': np.around(AvePrecision[10:
↪], 2),
                                'Average F1measure': 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_tfidf = compute_RP_yaxis(Precision=AvePrecision, Recall=AveRecall)
plt.plot(x_axis, y_axis_tfidf, '-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_tfidf_avg = y_axis_tfidf
```

```
Results for top n docs returned for each query:
+--------+-------------------------------------------------------+----------------
```

Query	Recall@1~10	Precision@1~10	F1measure@1~10
Query1	[0.06 0.12 0.12 0.19 0.25 0.31 0.38 0.44 0.5 0.56]	[1. 1. 0.67 0.75 0.8 0.83 0.86 0.88 0.89 0.9]	[0.12 0.22 0.21 0.3 0.38 0.45 0.52 0.58 0.64 0.69]
Query2	[0. 0. 0. 0. 0.17 0.17 0.17 0.17 0.17 0.17]	[0. 0. 0. 0. 0.2 0.17 0.14 0.12 0.11 0.1]	[0. 0. 0. 0. 0.18 0.17 0.15 0.14 0.13 0.12]
Query3	[0. 0.07 0.07 0.14 0.14 0.14 0.14 0.14 0.21 0.21]	[0. 0.5 0.33 0.5 0.4 0.33 0.29 0.25 0.33 0.3]	[0. 0.12 0.12 0.22 0.21 0.2 0.19 0.18 0.26 0.25]
Query4	[0. 0.07 0.14 0.21 0.29 0.36 0.43 0.5 0.5 0.5]	[0. 0.5 0.67 0.75 0.8 0.83 0.86 0.88 0.78 0.7]	[0. 0.12 0.24 0.33 0.42 0.5 0.57 0.64 0.61 0.58]
Query5	[0. 0.2 0.4 0.4 0.4 0.4 0.4 0.4 0.4 0.4]	[0. 0.5 0.67 0.5 0.4 0.33 0.29 0.25 0.22 0.2]	[0. 0.29 0.5 0.44 0.4 0.36 0.33 0.31 0.29 0.27]
Query6	[0.08 0.17 0.25 0.33 0.42 0.42 0.42 0.42 0.5 0.58]	[1. 1. 1. 1. 1. 0.83 0.71 0.62 0.67 0.7]	[0.15 0.29 0.4 0.5 0.59 0.56 0.53 0.5 0.57 0.64]
Query7	[0.07 0.14 0.14 0.21 0.29 0.36 0.43 0.5 0.57 0.57]	[1. 1. 0.67 0.75 0.8 0.83 0.86 0.88 0.89 0.8]	[0.13 0.25 0.24 0.33 0.42 0.5 0.57 0.64 0.7 0.67]
Query8	[0.08 0.15 0.23 0.31 0.38 0.46 0.54 0.54 0.62 0.69]	[1. 1. 1. 1. 1. 1. 1. 0.88 0.89 0.9]	[0.14 0.27 0.38 0.47 0.56 0.63 0.7 0.67 0.73 0.78]



Query	Average Recall	Average Precision	Average F1measure
1	0.52	0.58	0.53
2	0.54	0.55	0.53
3	0.56	0.53	0.53
4	0.59	0.52	0.54
5	0.6	0.5	0.53
6	0.61	0.48	0.52
7	0.65	0.47	0.53
8	0.66	0.45	0.52
9	0.68	0.44	0.52
10	0.68	0.42	0.51



Evaluating each query by comparing their metrics against the Average

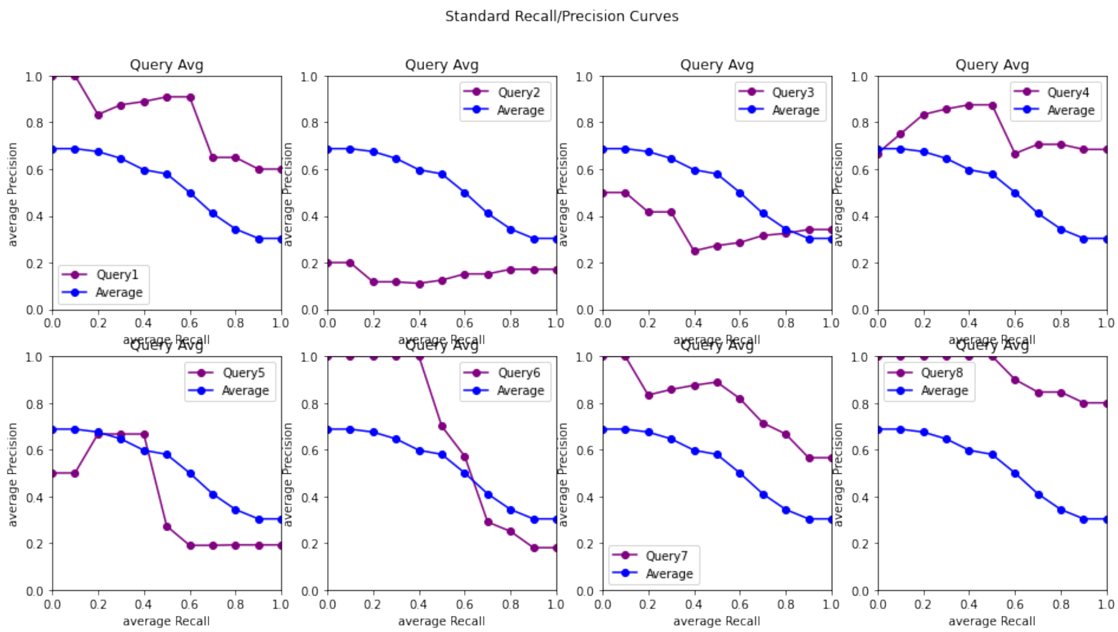
[12]:
```
import warnings
warnings.filterwarnings('ignore')

# Initialize the figure
fig, axs = plt.subplots(2, 4, figsize=(16, 8))
fig.suptitle('Standard Recall/Precision Curves')

re_ID =␣
↪[[36164,58481,26246,2033,48779,34523,9726,56494,49525,45278,35694,41876,17309,11135,17273,1
        [57123,25299,55017,7432,2114,40871],
        ␣
↪[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
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: ", np.around(Recall[:10],2))
  print("Precision: ", np.around(Precision[:10],2))
  print("F1measure: ", 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()
```

```
Query1: The ring is a great gift. My friend loves it
Recall:  [0.06 0.12 0.12 0.19 0.25 0.31 0.38 0.44 0.5  0.56]
Precision:  [1.   1.   0.67 0.75 0.8  0.83 0.86 0.88 0.89 0.9 ]
F1measure:  [0.12 0.22 0.21 0.3  0.38 0.45 0.52 0.58 0.64 0.69]

Query2: horrible bad quality bracelet
Recall:  [0.   0.   0.   0.   0.17 0.17 0.17 0.17 0.17 0.17]
```

```
Precision:  [0.   0.   0.   0.   0.2  0.17 0.14 0.12 0.11 0.1 ]
F1measure:  [0.   0.   0.   0.   0.18 0.17 0.15 0.14 0.13 0.12]

Query3: arrived promptly and happy with the seller
Recall:  [0.   0.07 0.07 0.14 0.14 0.14 0.14 0.14 0.21 0.21]
Precision:  [0.   0.5  0.33 0.5  0.4  0.33 0.29 0.25 0.33 0.3 ]
F1measure:  [0.   0.12 0.12 0.22 0.21 0.2  0.19 0.18 0.26 0.25]

Query4: wear it with casual wear
Recall:  [0.   0.07 0.14 0.21 0.29 0.36 0.43 0.5  0.5  0.5 ]
Precision:  [0.   0.5  0.67 0.75 0.8  0.83 0.86 0.88 0.78 0.7 ]
F1measure:  [0.   0.12 0.24 0.33 0.42 0.5  0.57 0.64 0.61 0.58]

Query5: i expected better quality. i will return this item
Recall:  [0.  0.2 0.4 0.4 0.4 0.4 0.4 0.4 0.4 0.4]
Precision:  [0.   0.5  0.67 0.5  0.4  0.33 0.29 0.25 0.22 0.2 ]
F1measure:  [0.   0.29 0.5  0.44 0.4  0.36 0.33 0.31 0.29 0.27]

Query6: looks beautiful. The design is pretty. pefect and color is light
Recall:  [0.08 0.17 0.25 0.33 0.42 0.42 0.42 0.42 0.5  0.58]
Precision:  [1.   1.   1.   1.   1.   0.83 0.71 0.62 0.67 0.7 ]
F1measure:  [0.15 0.29 0.4  0.5  0.59 0.56 0.53 0.5  0.57 0.64]

Query7: This ring looks nothing like the picture. the diamonds are small and not
very noticeable
Recall:  [0.07 0.14 0.14 0.21 0.29 0.36 0.43 0.5  0.57 0.57]
Precision:  [1.   1.   0.67 0.75 0.8  0.83 0.86 0.88 0.89 0.8 ]
F1measure:  [0.13 0.25 0.24 0.33 0.42 0.5  0.57 0.64 0.7  0.67]

Query8: braclet looked just like its picture and is nice quality sterling
silver.
Recall:  [0.08 0.15 0.23 0.31 0.38 0.46 0.54 0.54 0.62 0.69]
Precision:  [1.   1.   1.   1.   1.   1.   1.   0.88 0.89 0.9 ]
F1measure:  [0.14 0.27 0.38 0.47 0.56 0.63 0.7  0.67 0.73 0.78]
```



Tune Tf (Sublinear) and SVD dimension of 3

[13]:
```
# Define tuning parameters for weighthing schemes and SVD parameters
Xtrain_tf = _prepare_data(reviews, 'tf', vocab)
trunc_SVD_model_tf = TruncatedSVD(n_components=3)
approx_Xtrain_tf = trunc_SVD_model_tf.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],
          ␣
 ↪[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()
```

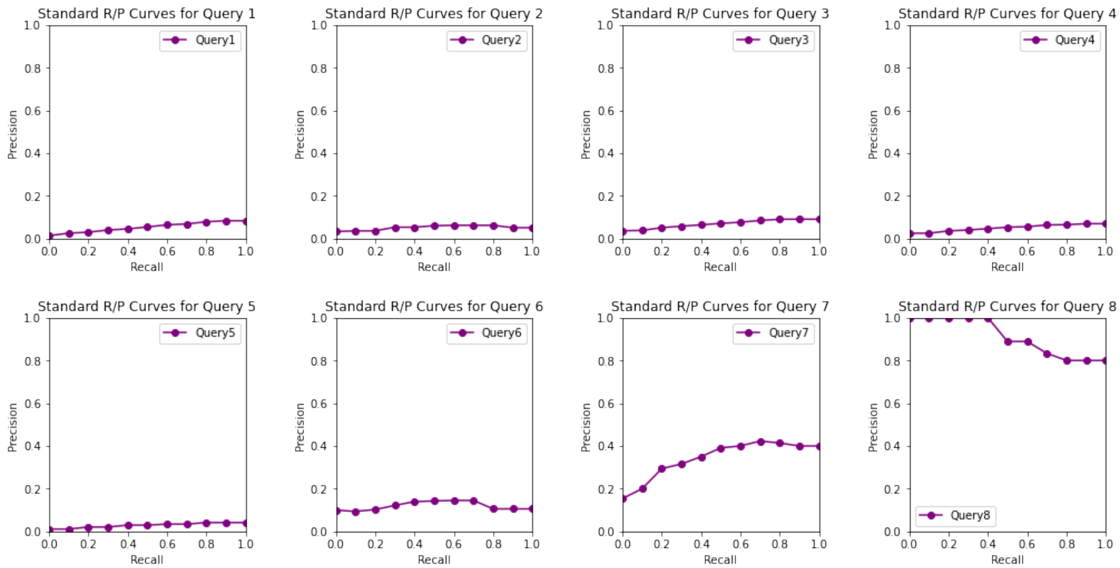
```python
_y_axis_lsi_tf = list()


# 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', 'Recall', 'Precision', 'F1measure'])

# loop queries
j = 0
for query in querys:
  # retrieval
  encoded_query_tf = _preprocess_query(query, 'tf', vocab)
  transformed_query_tf = trunc_SVD_model_tf.transform(encoded_query)
  similarities_tf = cosine_similarity(approx_Xtrain_tf, transformed_query_tf)

  # rank the index
  indexes_tf = np.argsort(similarities_tf.flat)[::-1]
  doc_id = [data.iloc[indexes_tf[i]]['ID'] for i in range(len(indexes_tf))]

  # Mark the relevant index
  re_mark = []
  for i in range(len(indexes_tf)):
    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_tf, Precision_tf, F1measure_tf = 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_tf[:10], 2), np.
 ↪around(Precision_tf[:10], 2), np.around(F1measure_tf[:10], 2)]
  # save
  AllRecall.append(Recall_tf)
  AllPrecision.append(Precision_tf)
  AllF1measure.append(F1measure_tf)

  # Plot R/P curve in the subplot
  x_axis = np.linspace(0, 1, 11)
  y_axis = compute_RP_yaxis(Precision=Precision_tf, Recall=Recall_tf)
```

```
    _y_axis_lsi_tf.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_tf = np.array(AllRecall)
AllPrecision_tf = np.array(AllPrecision)
AllF1measure_tf = np.array(AllF1measure)
AveRecall_tf = (AllRecall_tf[0] + AllRecall_tf[1] + AllRecall_tf[2] +␣
 ↪AllRecall_tf[3] + AllRecall_tf[4] + AllRecall_tf[5] + AllRecall_tf[6] +␣
 ↪AllRecall_tf[7])/8
AvePrecision_tf = (AllPrecision_tf[0] + AllPrecision_tf[1]+AllPrecision_tf[2] +␣
 ↪AllPrecision_tf[3]+AllPrecision_tf[4] + AllPrecision_tf[5] +␣
 ↪AllPrecision_tf[6] + AllPrecision_tf[7])/8
AveF1measure_tf = (AllF1measure_tf[0] + AllF1measure_tf[1]+AllF1measure_tf[2] +␣
 ↪AllF1measure_tf[3]+AllF1measure_tf[4] + AllF1measure_tf[5] +␣
 ↪AllF1measure_tf[6] + AllF1measure_tf[7])/8

# Create a DataFrame for average results
avg_results_tf = pd.DataFrame({'Average Recall': np.around(AveRecall_tf[10:],␣
 ↪2),
                                'Average Precision': np.
 ↪around(AvePrecision_tf[10:], 2),
                                'Average F1measure': np.
 ↪around(AveF1measure_tf[10:], 2)})

plot_avg_table(avg_results_tf.iloc[:10])

# Plot average R/P curve
x_axis = np.linspace(0, 1, 11)
```

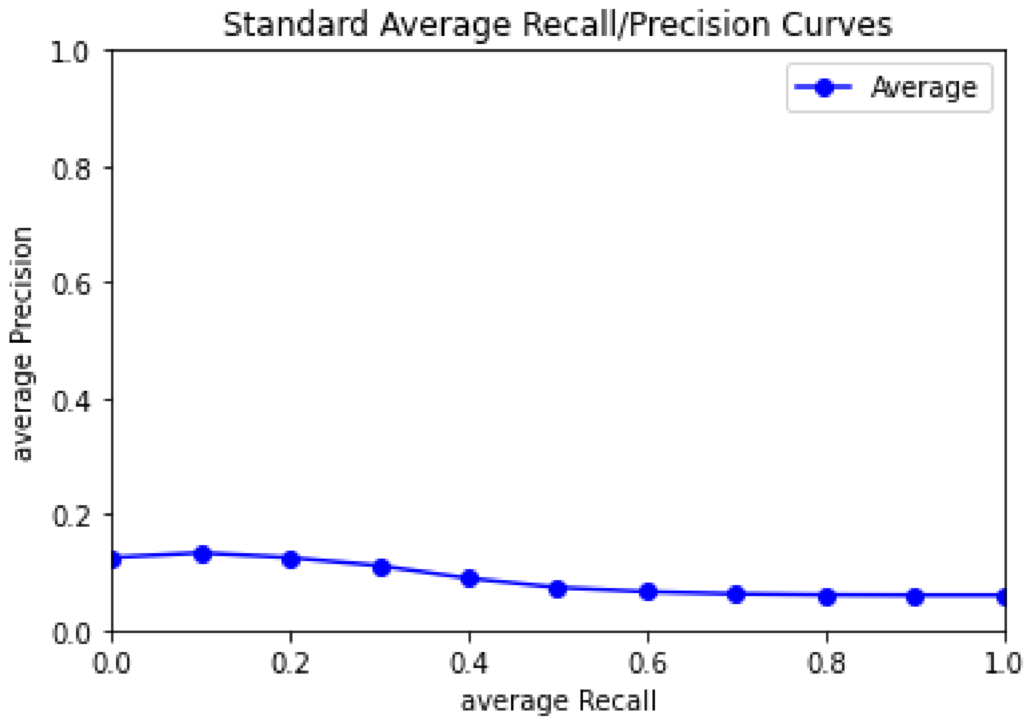
```
y_axis_tf = compute_RP_yaxis(Precision=AvePrecision_tf, Recall=AveRecall_tf)
plt.plot(x_axis, y_axis_tf, '-bo', color="blue", label="Average")
plt.xlim(0, 1)
plt.ylim(0, 1)
plt.xlabel('average Recall')
plt.ylabel('average Precision')
plt.title('Standard Average Recall/Precision Curves')
plt.legend()
plt.show()

LSI_tf_avg = y_axis_tf
```

```
Results for top n docs returned for each query:
+--------+-----------------------------------------------------+----------------
------------------------------------+-----------------------------------------
-----------+
| Query  |                     Recall@1~10                     |
Precision@1~10                    |                    F1measure@1~10
|
+--------+-----------------------------------------------------+----------------
------------------------------------+-----------------------------------------
-----------+
| Query1 |           [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. 0. 0.
0.]           |
| 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. 0. 0.
0.]           |
| Query3 |           [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. 0. 0.
0.]           |
| Query4 |           [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. 0. 0.
0.]           |
| Query5 |           [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. 0. 0.
0.]           |
| Query6 | [0.   0.   0.   0.   0.   0.   0.   0.   0.   0.08] |      [0.  0.
0.  0.  0.  0.  0.  0.  0.  0.1]      | [0.   0.   0.   0.   0.   0.   0.   0.
0.   0.09] |
| Query7 | [0.   0.   0.   0.   0.   0.   0.07 0.07 0.07 0.07] | [0.   0.   0.
0.   0.   0.   0.14 0.12 0.11 0.1 ] | [0.   0.   0.   0.   0.   0.   0.1  0.09
0.09 0.08] |
| Query8 | [0.08 0.15 0.23 0.31 0.38 0.46 0.46 0.54 0.62 0.62] | [1.   1.   1.
1.   1.   1.   0.86 0.88 0.89 0.8 ] | [0.14 0.27 0.38 0.47 0.56 0.63 0.6  0.67
0.73 0.7 ] |
```

```
+---------+------------------------------------------------------+---------------
--------------------------------------+--------------------------------------------
------------+
```



Query	Average Recall	Average Precision	Average F1measure
1	0.11	0.12	0.11
2	0.12	0.12	0.12
3	0.12	0.12	0.12
4	0.13	0.12	0.13
5	0.15	0.13	0.14
6	0.16	0.13	0.15
7	0.17	0.13	0.15
8	0.17	0.12	0.14
9	0.18	0.12	0.15
10	0.19	0.12	0.15



Comparing TF vs TFIDF The TFIDF retrieves a higher proportion of relevant documents while maintaining a higher precision, indicating a better recall-precision balance. The TF retrieval model, on the other hand, struggles to find relevant documents and has a higher rate of false positives. TFIDF is thus a more effective and accurate NLP LSI retrieval system than TF.

[14]:
```
from prettytable import PrettyTable

def plot_avg_table(df1, df2):
    # Print the average results in a formatted table
    print("\nAverage Recall, average Precision, average F1-measure:")

    # Create a PrettyTable for average results
    avg_pt = PrettyTable()

    # Add columns to the PrettyTable
    avg_pt.field_names = ["Rank", "TF-IDF Recall", "TF-IDF Precision", "TF-IDF␣
↪F1measure",
                          "TF Recall", "TF Precision", "TF F1measure"]

    # Add rows from both DataFrames to the PrettyTable
    for index, (row1, row2) in enumerate(zip(df1.iterrows(), df2.iterrows())):
        _, row1 = row1
        _, row2 = row2
```

```
        avg_pt.add_row([index + 1,
                        row1['Average Recall'], row1['Average Precision'],␣
 ↪row1['Average F1measure'],
                        row2['Average Recall'], row2['Average Precision'],␣
 ↪row2['Average F1measure']])

    # Print the PrettyTable for average results
    print(avg_pt)

# Call the function with the top 10 rows of the DataFrames
plot_avg_table(avg_results_df.iloc[:10], avg_results_tf.iloc[:10])
```

```
Average Recall, average Precision, average F1-measure:
+------+---------------+------------------+------------------+-----------+------
--------+--------------+
| Rank | TF-IDF Recall | TF-IDF Precision | TF-IDF F1measure | TF Recall | TF
Precision | TF F1measure |
+------+---------------+------------------+------------------+-----------+------
--------+--------------+
|  1   |      0.52     |       0.58       |       0.53       |    0.11   |
0.12     |     0.11     |
|  2   |      0.54     |       0.55       |       0.53       |    0.12   |
0.12     |     0.12     |
|  3   |      0.56     |       0.53       |       0.53       |    0.12   |
0.12     |     0.12     |
|  4   |      0.59     |       0.52       |       0.54       |    0.13   |
0.12     |     0.13     |
|  5   |      0.6      |       0.5        |       0.53       |    0.15   |
0.13     |     0.14     |
|  6   |      0.61     |       0.48       |       0.52       |    0.16   |
0.13     |     0.15     |
|  7   |      0.65     |       0.47       |       0.53       |    0.17   |
0.13     |     0.15     |
|  8   |      0.66     |       0.45       |       0.52       |    0.17   |
0.12     |     0.14     |
|  9   |      0.68     |       0.44       |       0.52       |    0.18   |
0.12     |     0.15     |
|  10  |      0.68     |       0.42       |       0.51       |    0.19   |
0.12     |     0.15     |
+------+---------------+------------------+------------------+-----------+------
--------+--------------+
```

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.

3.1 3a - Develop a neural retrieval model and compare with LSI model

[15]:
```
# load all docs in a directory
def __process_query(queries, vocab):
        lines = list()
        # walk through all files in the folder
        for doc in queries:
                # print(len(doc))
                line = doc_to_line(doc, vocab)
                # add to list
                lines.append(line)
        return lines

train_docs = reviews
query_docs = __process_query(querys, vocab)

train_docs = pd.Series(train_docs)
query_docs = pd.Series(query_docs)

# print(train_docs.shape)
# print(test_docs.shape)
```

[16]:
```
!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 (4.27.3)
Requirement already satisfied: regex!=2019.12.17 in
/usr/local/lib/python3.9/dist-packages (from transformers) (2022.10.31)
Requirement already satisfied: packaging>=20.0 in /usr/local/lib/python3.9/dist-
packages (from transformers) (23.0)
Requirement already satisfied: filelock in /usr/local/lib/python3.9/dist-
```

```
packages (from transformers) (3.10.0)
Requirement already satisfied: pyyaml>=5.1 in /usr/local/lib/python3.9/dist-
packages (from transformers) (6.0)
Requirement already satisfied: huggingface-hub<1.0,>=0.11.0 in
/usr/local/lib/python3.9/dist-packages (from transformers) (0.13.3)
Requirement already satisfied: tqdm>=4.27 in /usr/local/lib/python3.9/dist-
packages (from transformers) (4.65.0)
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: 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: 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)
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: certifi>=2017.4.17 in
/usr/local/lib/python3.9/dist-packages (from requests->transformers) (2022.12.7)
```

[17]:
```
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')
```

[18]:
```
# Loading the Pre-trained BERT model
# For DistilBERT:
model_class, tokenizer_class, pretrained_weights = (ppb.DistilBertModel, ppb.
 ↪DistilBertTokenizer, 'distilbert-base-uncased')

## Want BERT instead of distilBERT? Uncomment the following line:
#model_class, tokenizer_class, pretrained_weights = (ppb.BertModel, ppb.
 ↪BertTokenizer, 'bert-base-uncased')

# Load pretrained model/tokenizer
tokenizer = tokenizer_class.from_pretrained(pretrained_weights)
```

```
model = model_class.from_pretrained(pretrained_weights)
```

```
Some weights of the model checkpoint at distilbert-base-uncased were not used
when initializing DistilBertModel: ['vocab_transform.weight',
'vocab_transform.bias', 'vocab_projector.weight', 'vocab_layer_norm.bias',
'vocab_layer_norm.weight', 'vocab_projector.bias']
- 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 from a BertForSequenceClassification model).
```

[19]:
```
N = len(train_docs)

with torch.no_grad():
    # Tokenization
    tokenized = train_docs[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)

    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
```

[20]:
```
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])
8
```

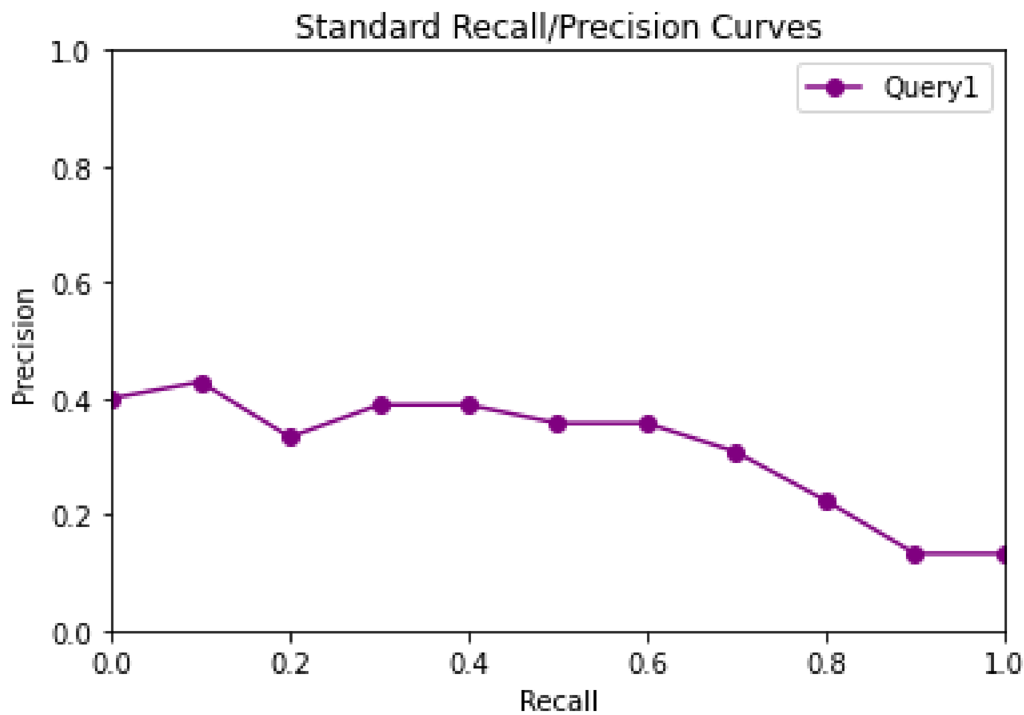
[21]:

```
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)
```

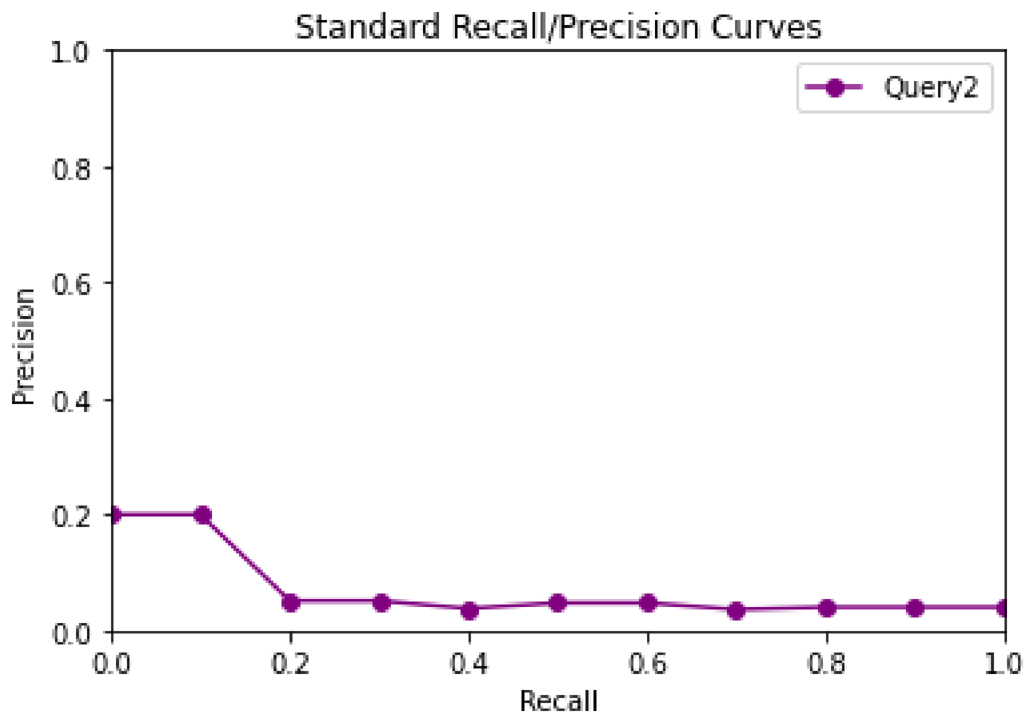
```
    BERT_F1measure = np.array(BERT_F1measure)
    # print(re_mark)
    print("Recall@1~10: ", np.around(BERT_Recall[:10],2))
    print("Precision@1~10: ", np.around(BERT_Precision[:10],2))
    print("F1measure@1~10: ", np.around(BERT_F1measure[:10],2))

    # 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 Recall@1~10: ", 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
```

```python
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
```

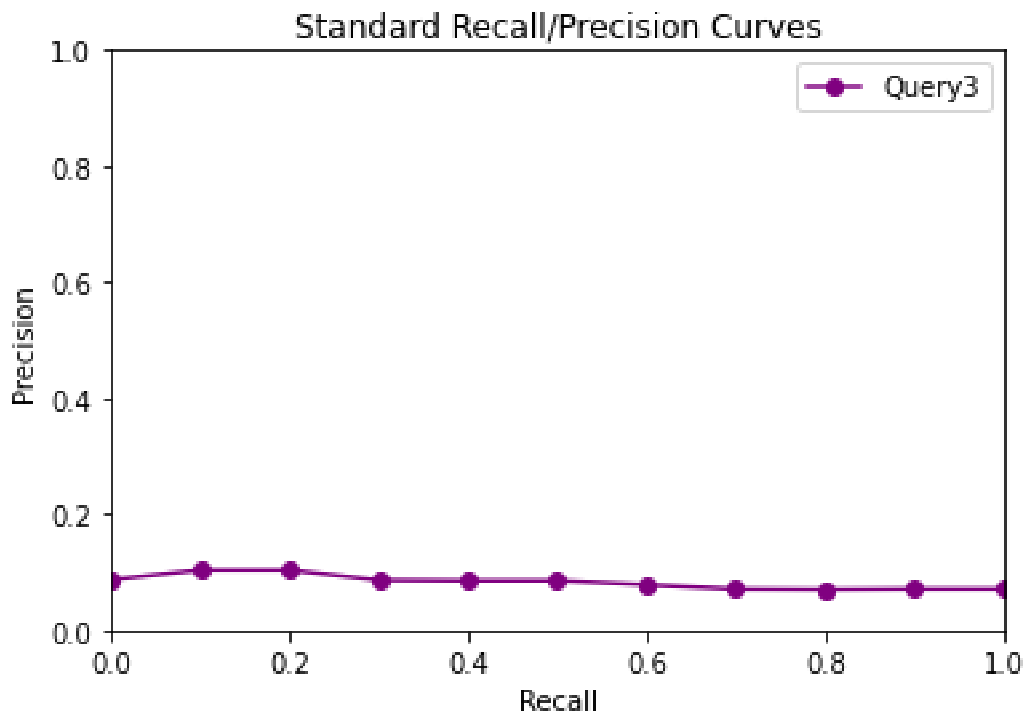
```
Query1: braclet looked just like its picture and is nice quality sterling
silver.
Top 1 result: ID48216  imagine adoring ring love got birthday woman
Top 2 result: ID45203  imagine adoring ring love got birthday woman
Top 3 result: ID6421  pinky need love find size flower perfect hard nice nt
rings ring
Top 4 result: ID48779  got thing love gift rings ring
Top 5 result: ID58481  wife ring cheap great high loves gift quality
Top 6 result: ID17442  wonderful sending eve daughter beautiful addiction thank
ring
Top 7 result: ID26246  received birthday gift happy loves ring
Top 8 result: ID58595  ring absolutely love got engagement beautiful durable
Top 9 result: ID1185  holds wedding love every gorgeous sits ring night
Top 10 result: ID6522  jewelry ring collection love suggest every
Recall@1~10:  [0.   0.   0.   0.06 0.12 0.12 0.19 0.19 0.19 0.19]
Precision@1~10:  [0.   0.   0.   0.25 0.4  0.33 0.43 0.38 0.33 0.3 ]
F1measure@1~10:  [0.   0.   0.   0.1  0.19 0.18 0.26 0.25 0.24 0.23]
```



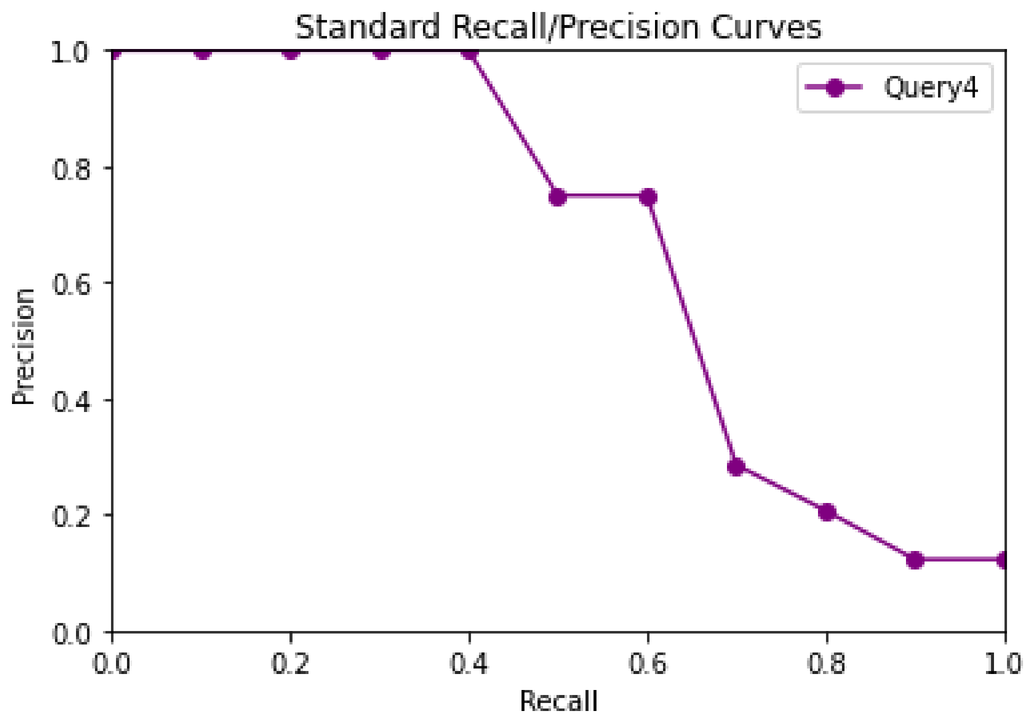

```
Query2: braclet looked just like its picture and is nice quality sterling
silver.
Top 1 result: ID2134  wearing
Top 2 result: ID9050  ring metal enough pretty easily
Top 3 result: ID50197  beautiful smooth look
Top 4 result: ID52663  comfortable see wear ring quite please
Top 5 result: ID57123  even close bracelet quality appearance disappointed
definitely worth
Top 6 result: ID19944  use pleased shipping purchase
Top 7 result: ID45548  item small high attractive quality
Top 8 result: ID49720  absolutely anyone would recommend beautiful amethyst ring
stunning
Top 9 result: ID6522  jewelry ring collection love suggest every
Top 10 result: ID26246  received birthday gift happy loves ring
Recall@1~10:  [0.   0.   0.   0.   0.17 0.17 0.17 0.17 0.17 0.17]
Precision@1~10:  [0.   0.   0.   0.   0.2  0.17 0.14 0.12 0.11 0.1 ]
F1measure@1~10:  [0.   0.   0.   0.   0.18 0.17 0.15 0.14 0.13 0.12]
```



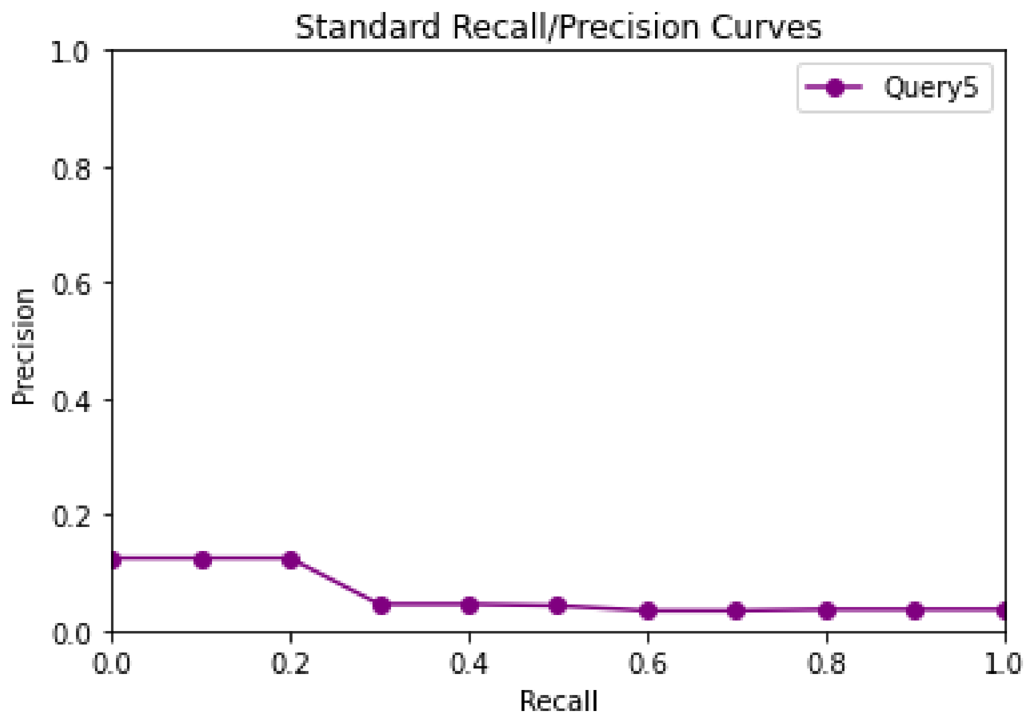

```
Query3: braclet looked just like its picture and is nice quality sterling
silver.
Top 1 result: ID22058  came item great recommend happy promptly quality
Top 2 result: ID28474  lovely wear ring advertised pinky actually thumb
Top 3 result: ID30926  timely manner garnet looks would recommend ring
Top 4 result: ID32674  hoped quality ever wonderful could item surprise much
Top 5 result: ID57123  even close bracelet quality appearance disappointed
definitely worth
Top 6 result: ID6522  jewelry ring collection love suggest every
Top 7 result: ID17442  wonderful sending eve daughter beautiful addiction thank
ring
Top 8 result: ID28250  one know love beyond gorgeous rings like ring wanted
Top 9 result: ID10535  one know love beyond gorgeous rings like ring wanted
Top 10 result: ID52663  comfortable see wear ring quite please
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. 0.]
F1measure@1~10:  [0. 0. 0. 0. 0. 0. 0. 0. 0. 0.]
```



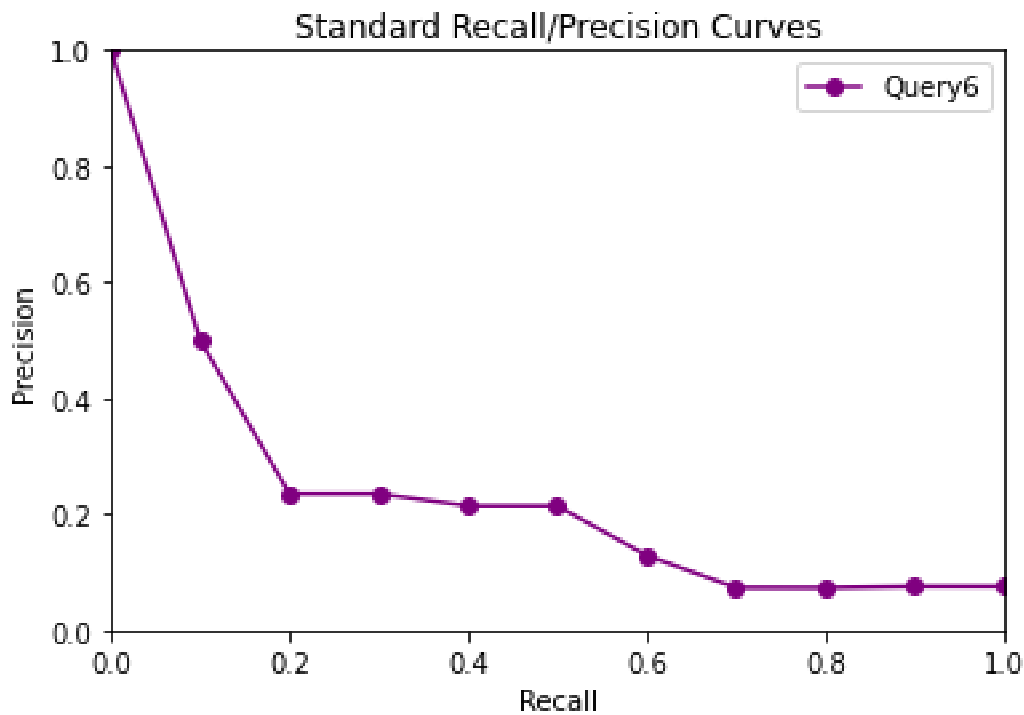

```
Query4: braclet looked just like its picture and is nice quality sterling
silver.
Top 1 result: ID19852  good wear everyday
Top 2 result: ID53660  want something wear nice comfortable casual
Top 3 result: ID30640  enough suit detail perfect wear nice colors
Top 4 result: ID37486  going work pendant wear nt casual
Top 5 result: ID44126  catch wear style comfortable stones light
Top 6 result: ID2134  wearing
Top 7 result: ID11087  favorite wear mine wanted
Top 8 result: ID50197  beautiful smooth look
Top 9 result: ID52663  comfortable see wear ring quite please
Top 10 result: ID56330  wearing great way without
Recall@1~10:  [0.07 0.14 0.21 0.29 0.36 0.43 0.43 0.43 0.43 0.5 ]
Precision@1~10:  [1.   1.   1.   1.   1.   1.   0.86 0.75 0.67 0.7 ]
F1measure@1~10:  [0.13 0.25 0.35 0.44 0.53 0.6  0.57 0.55 0.52 0.58]
```



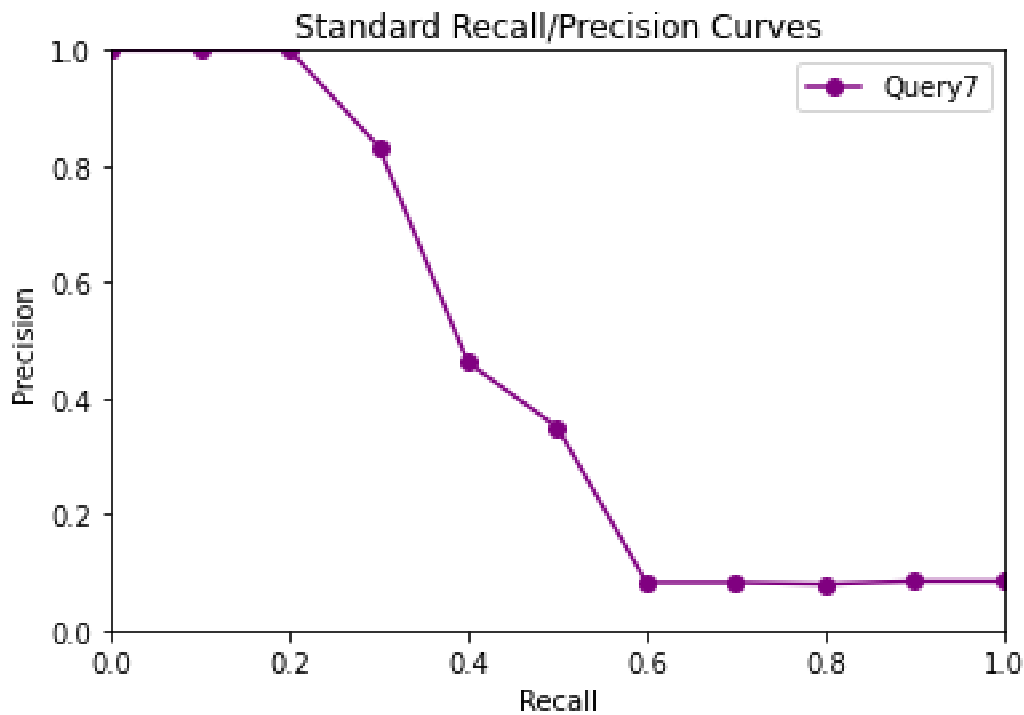

```
Query5: braclet looked just like its picture and is nice quality sterling
silver.
Top 1 result: ID1816  item would recommend look quality
Top 2 result: ID45548  item small high attractive quality
Top 3 result: ID22058  came item great recommend happy promptly quality
Top 4 result: ID19852  good wear everyday
Top 5 result: ID57123  even close bracelet quality appearance disappointed
definitely worth
Top 6 result: ID19944  use pleased shipping purchase
Top 7 result: ID30926  timely manner garnet looks would recommend ring
Top 8 result: ID13373  seller quality poor item pictured
Top 9 result: ID17304  purchased service several excellent customer first items
Top 10 result: ID38305  quality high see item would charm fan
Recall@1~10:  [0.  0.  0.  0.  0.  0.  0.  0.2 0.2 0.2]
Precision@1~10:  [0.   0.   0.   0.   0.   0.   0.   0.12 0.11 0.1 ]
F1measure@1~10:  [0.   0.   0.   0.   0.   0.   0.   0.15 0.14 0.13]
```



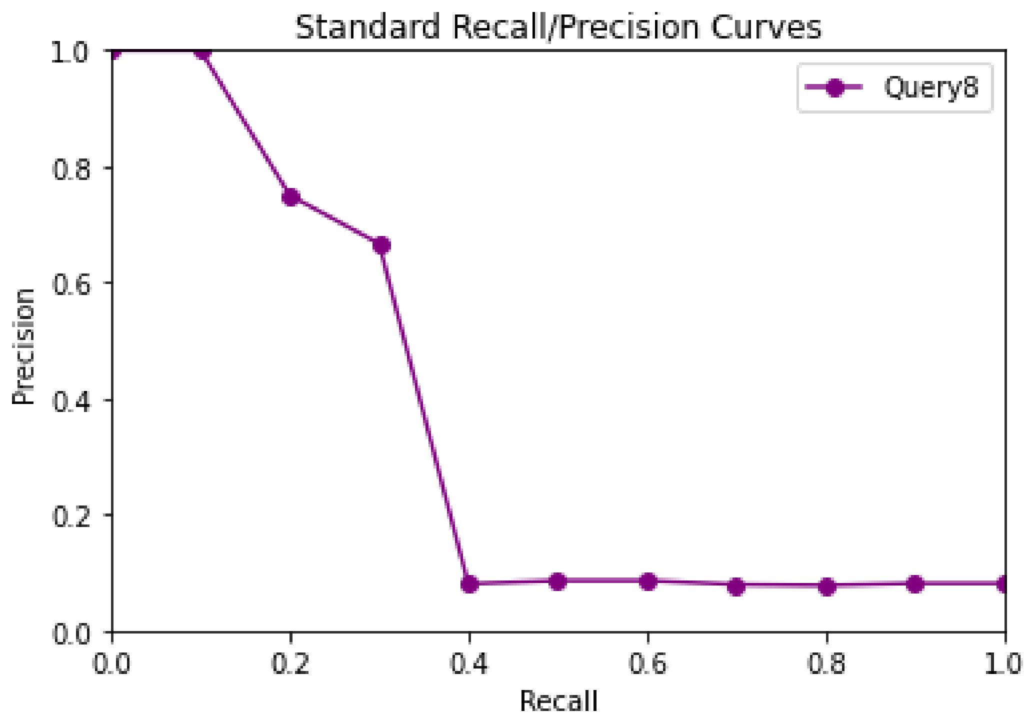

```
Query6: braclet looked just like its picture and is nice quality sterling
silver.
Top 1 result: ID52375  present looks color bought nice pretty
Top 2 result: ID44490  small quality good light size nice picture like described
look
Top 3 result: ID17166  well money delicate pretty beautiful think worth yet
necklace look simple
Top 4 result: ID39932  absolutely heart looks amazing pendant beautiful colors
dainty price
Top 5 result: ID642  like nice sterling silver picture looked quality
Top 6 result: ID3865  dainty looking sparkle pretty
Top 7 result: ID30640  enough suit detail perfect wear nice colors
Top 8 result: ID37794  comfortable quality good stones light polished picture
like earrings price silver look
Top 9 result: ID2131  piece work hand wearing gold right wear looking wanted
Top 10 result: ID10642  purple clear picture like looked
Recall@1~10:  [0.08 0.08 0.08 0.17 0.17 0.17 0.17 0.17 0.17 0.17]
Precision@1~10:  [1.   0.5  0.33 0.5  0.4  0.33 0.29 0.25 0.22 0.2 ]
F1measure@1~10:  [0.15 0.14 0.13 0.25 0.24 0.22 0.21 0.2  0.19 0.18]
```



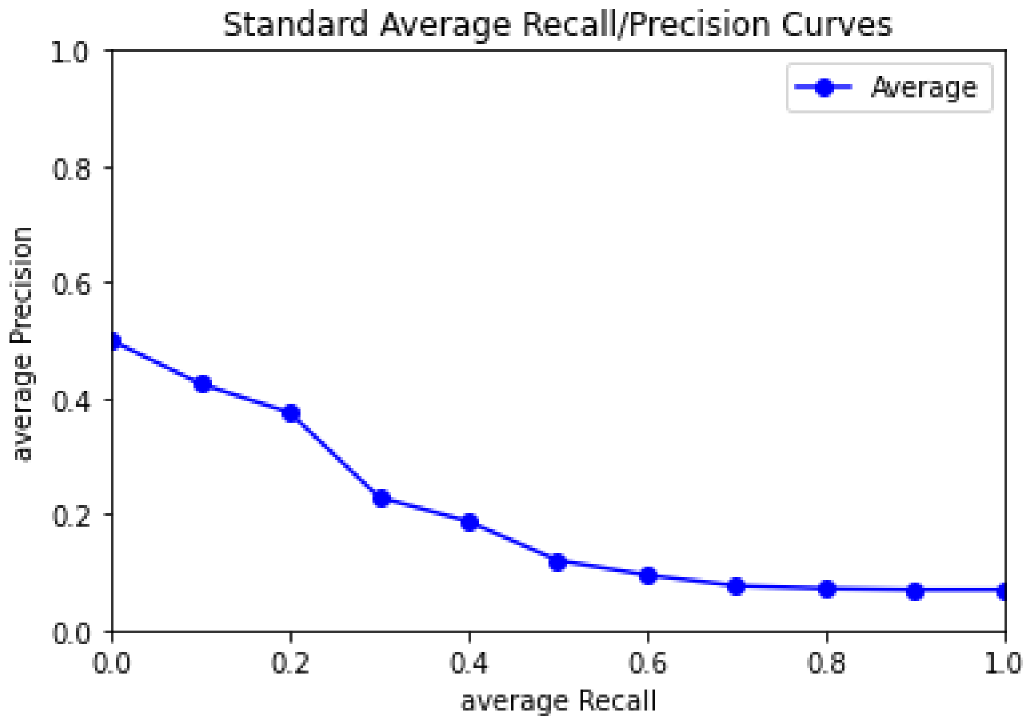

```
Query7: braclet looked just like its picture and is nice quality sterling
silver.
Top 1 result: ID209  small sending looks diamonds picture nothing like back ring
Top 2 result: ID36165  person small smaller size diamonds make disappointed
little like ring alot pictures look
Top 3 result: ID28542  garnet one large nice picture another like ring crack
chip looked
Top 4 result: ID10642  purple clear picture like looked
Top 5 result: ID38637  received got heart looks make disappointed picture little
smooth looked like ring look shape
Top 6 result: ID216  even small barely returned looks stones thin buy promptly
tell picture would nothing rings like misleading ring
Top 7 result: ID12358  seen know high beautiful like quite price look
Top 8 result: ID53409  like metal sterling silver picture looks although
description beads
Top 9 result: ID52837  sparkling around forward imagine pretty looking toe
Top 10 result: ID17166  well money delicate pretty beautiful think worth yet
necklace look simple
Recall@1~10:  [0.07 0.14 0.21 0.21 0.29 0.36 0.36 0.36 0.36 0.36]
Precision@1~10:  [1.   1.   1.   0.75 0.8  0.83 0.71 0.62 0.56 0.5 ]
F1measure@1~10:  [0.13 0.25 0.35 0.33 0.42 0.5  0.48 0.45 0.43 0.42]
```




```
Query8: braclet looked just like its picture and is nice quality sterling
silver.
Top 1 result: ID642  like nice sterling silver picture looked quality
Top 2 result: ID3494  like nice looks picture
Top 3 result: ID57123  even close bracelet quality appearance disappointed
definitely worth
Top 4 result: ID10642  purple clear picture like looked
Top 5 result: ID50197  beautiful smooth look
Top 6 result: ID44490  small quality good light size nice picture like described
look
Top 7 result: ID38305  quality high see item would charm fan
Top 8 result: ID2185  small looks toy way nice would recommend want like ring
Top 9 result: ID3865  dainty looking sparkle pretty
Top 10 result: ID9050  ring metal enough pretty easily
Recall@1~10:  [0.08 0.15 0.15 0.23 0.23 0.31 0.31 0.31 0.31 0.31]
Precision@1~10:  [1.   1.   0.67 0.75 0.6  0.67 0.57 0.5  0.44 0.4 ]
F1measure@1~10:  [0.14 0.27 0.25 0.35 0.33 0.42 0.4  0.38 0.36 0.35]
```




```
Average Recall, average Precision, average F1-measure:
average Recall@1~10:  [0.04 0.07 0.08 0.12 0.17 0.19 0.2  0.23 0.23 0.24]
average Precision@1~10:  [0.5  0.44 0.37 0.41 0.42 0.42 0.38 0.34 0.31 0.29]
average F1measure@1~10:  [0.07 0.11 0.14 0.19 0.24 0.26 0.26 0.27 0.25 0.25]
```

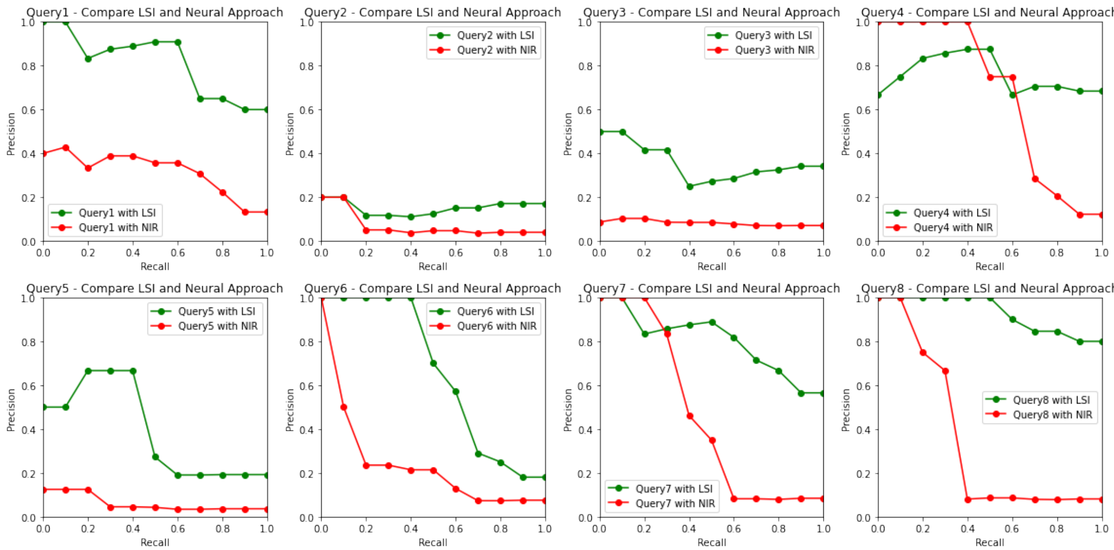


3a Comparisim of NIR & LSI

[22]:
```
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 with␣
 ↪LSI"%(index+1))
    ax.plot(x_axis, plot_NIR, '-bo', color="red", label="Query%d with␣
 ↪NIR"%(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	0.91	0.5	0.36	0.5
horrible bad quality bracelet	0.12	0.5	0.05	0.5
arrived promptly and happy with the seller	0.27	0.5	0.09	0.5
wear it with casual wear	0.88	0.5	0.75	0.5
i expected better quality. i will return this item	0.27	0.5	0.04	0.5
looks beautiful. The design is pretty. pefect and color is light	0.7	0.5	0.21	0.5
This ring looks nothing like the picture. the diamonds are small and not very noticeable	0.89	0.5	0.35	0.5
braclet looked just like its picture and is nice quality sterling silver.	1.0	0.5	0.09	0.5

The LSI model achieves a better balance of recall and precision because it retrieves relevant documents more accurately, resulting in fewer false positives. NIR, on the other hand, retrieves relevant documents less accurately, resulting in a higher rate of false positives.

3.2 3b - An Interactive interface for users to type in their own query

[23]:
```
# Build funtion to convert queries to embedded representations using NIR
def build_nir_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

# Build funtion to convert queries to embedded representations using LSI
def build_lsi_query_embedding(query, n):
  encoded_query = preprocess_query(query, 'tfidf', vocab)
  # print(encoded_query.shape)
  transformed_query = trunc_SVD_model.transform(encoded_query)
  return transformed_query
```

[24]:

```python
from prettytable import PrettyTable, ALL

def search_nir(query, n_results=5):
  # Get the query embedding using the BERT-based model
  embedding = build_nir_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␣
↪similarity score
  indexes = np.argsort(similarity, axis=None)[::-1][:n_results]

  # Get the document IDs, texts, and similarity scores of the top n_results␣
↪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"] = "l"
  results.align["Similarity Score"] = "c"
  results.align["Text"] = "l"
  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)
```

```
def search_lsi(query, n_results=5):
  # Get the query embedding using the LSI-based model
  lsi_embedding = build_lsi_query_embedding(query, n_results)
  # Calculate the cosine similarity between the query embedding and the␣
↪document embeddings
  similarity = cosine_similarity(Xtrain, lsi_embedding)

  # indexes = np.argsort(similarities.flat)[-n_results:]
  # Get the indexes of the top n_results most similar documents sorted by␣
↪similarity score
  indexes = np.argsort(similarity, axis=None)[::-1][:n_results]

  # Get the document IDs, texts, and similarity scores of the top n_results␣
↪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]


  # print('_'*100)
  # print(f'Query: {query}')
  # print('='*100)
  # print(f"Top {n_results} documents retrieved:  {str(doc_id)}")
  # print('='*100)
  # for i in range(Top_n_reviews, 0, -1):
  #   print("Doc ID: " + str(indexes[-i]))
  #   # print("ID"+ str(data.iloc[indexes[i]]))
  #   print(reviews[indexes[-i]])
  #   print(docs[indexes[-i]])

  # Return the query IDs, document IDs, document texts, and similarity scores
  return d_id, ndoc_id, ndoc_text, similarity_scores
```

[25]:
```
n_results = 10 #@param {type:"slider", min:1, max:10, step:1}
# Get the query and rank from the user using input forms
```

[ ]:
```
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_nir(query, n_results)
print_search_results(_id, doc_id, doc_text, similarity)
```

Interactive Search Using LSI

```
[ ]: # _id_lsi, ndoc_id_lsi, doc_text_lsi, similarity_lsi = search_lsi(query,␣
      ↪n_results)
```

Fetch top 10 for each query in the query list

```
[ ]: 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␣
      ↪not very noticeable',
                'braclet looked just like its picture and is nice quality sterling␣
      ↪silver.'
     ]
       # Build Corpus list for use in Text sumarization. This was done here because␣
      ↪the installation of Summertime messes up my environment

     corpus_list = list()

     for index, query in enumerate(queries):
       query_id, query_doc_id, query_doc_text, query_similarity = search_nir(query,␣
      ↪n_results)
       print('\n' + f"QUERY {index+1} - {query}")
       print_search_results(_id, doc_id, doc_text, similarity)
       corpus_list.append(query_doc_text)
```

4 4 - Topic Modelling

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

4a - Top n search results clustered them into topics

```
[ ]: from bertopic import BERTopic
     from umap import UMAP
     # Process data into a list
     def __process_data(queries, vocab):
             lines = list()
             # walk through all files in the folder
             for doc in queries:
                     # print(len(doc))
                     line = doc_to_line(doc, vocab)
                     # add to list
                     lines.append(line)
```

```
        return lines

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)
  return topic_object

def build_topic2(docs, corpus, n_results=50):

  umap_model = UMAP(n_neighbors=10,
                 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,␣
 ↪verbose=True)
  topic_model = BERTopic(umap_model=umap_model, language="english")
  topics, probs = topic_model.fit_transform(cleaned_docs)
  topic_object.append(topic_model)
  return topic_object
```

[ ]:
```
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
query = input("Enter your query to extract topics:")

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

[ ]:
```
freq = topic_model.get_topic_info(); freq.head(10)
```

Evaluate topics

[ ]:
```
topic_model.visualize_heatmap(n_clusters=2, width=1000, height=1000)
```

Visualize term score decline per topic

[ ]:
```
topic_model.visualize_term_rank()
```

View topics for each query in the Queries list

[ ]:
```
# 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_nir(query, n_results)
  # 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)
    # b = topic.visualize_topics(top_n_topics=10)
  for i in a:
    print(i)
    # topic.visualize_topics()
```

4b - Visualize the topics

Visualize Keywords in the document: By building a word cloud of the entire document, we are able to get an idea of the most frequently occuring words in the corpus

[28]:
```
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()
```


```
[41]: def build_viz(topic_model, n_results):
        _keywords = topic_model.visualize_barchart(top_n_topics=n_results)
        # b = topic_model.visualize_topics()
        _hierachy = topic_model.visualize_hierarchy(top_n_topics=n_results)
        return _keywords, _hierachy

      def _build_viz(topic_model, n_results):
        _keywords = topic_model.visualize_barchart(top_n_topics=n_results)
        _topics = topic_model.visualize_topics()
        _hierachy = topic_model.visualize_hierarchy(top_n_topics=n_results)
        return _keywords, _topics, _hierachy
```

[59]:
```
# 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}

query = input("Enter the query:")

_id_lsi, ndoc_id_lsi, doc_text_lsi, similarity_lsi = search_lsi(query)
```

```
Enter the query:This stunning ring is an absolute showstopper! The craftsmanship
is impeccable and the attention to detail is truly impressive. The design is
both elegant and unique, and the sparkling stones catch the light beautifully. I
have received so many compliments while wearing this ring and it has quickly
become one of my favorite pieces of jewelry. I highly recommend it to anyone
looking for a luxurious and eye-catching addition to their collection.
```

```
---------------------------------------------------------------------------
ValueError                                Traceback (most recent call last)
<ipython-input-59-a8a8a96f0292> in <module>
      5 query = input("Enter the query:")
      6
----> 7 _id_lsi, ndoc_id_lsi, doc_text_lsi, similarity_lsi = search_lsi(query)

<ipython-input-24-cca406e499ae> in search_lsi(query, n_results)
     48     lsi_embedding = build_lsi_query_embedding(query, n_results)
     49     # Calculate the cosine similarity between the query embedding and the
 ↪document embeddings
---> 50     similarity = cosine_similarity(Xtrain, lsi_embedding)
     51
     52     # indexes = np.argsort(similarities.flat)[-n_results:]

/usr/local/lib/python3.9/dist-packages/sklearn/metrics/pairwise.py in
 ↪cosine_similarity(X, Y, dense_output)
   1391     # to avoid recursive import
   1392
-> 1393     X, Y = check_pairwise_arrays(X, Y)
   1394
   1395     X_normalized = normalize(X, copy=True)

/usr/local/lib/python3.9/dist-packages/sklearn/metrics/pairwise.py in
 ↪check_pairwise_arrays(X, Y, precomputed, dtype, accept_sparse,
 ↪force_all_finite, copy)
    178             )
    179     elif X.shape[1] != Y.shape[1]:
--> 180         raise ValueError(

    181             "Incompatible dimension for X and Y matrices: "
    182             "X.shape[1] == %d while Y.shape[1] == %d" % (X.shape[1], Y.
 ↪shape[1])
```

```
ValueError: Incompatible dimension for X and Y matrices: X.shape[1] == 450 while
↪Y.shape[1] == 5
```

Visualize the Topic

Ran into difficulty with the **visualize_topics** method Showed some inconsistent behaviours and kept throwing an error. Sometimes, I got it to work, but not sure why it bugs out again. Room for more improvement.

[60]:
```
# Perform Search and retrieve the top search results

_id, doc_id, docs, similarity = search_nir(query, n_results)
# 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)
```

```
Batches:   0%|          | 0/4 [00:00<?, ?it/s]

2023-03-24 10:44:11,299 - BERTopic - Transformed documents to Embeddings
2023-03-24 10:44:15,660 - BERTopic - Reduced dimensionality
2023-03-24 10:44:16,537 - BERTopic - Clustered reduced embeddings
```

[61]:
```
topic_model.visualize_distribution(probs[n_results-1], min_probability=0.0001)
```

```
---------------------------------------------------------------------------
IndexError                                Traceback (most recent call last)
<ipython-input-61-167ac8772580> in <module>
----> 1 topic_model.visualize_distribution(probs[n_results-1], min_probability=0.
↪0001)

IndexError: index 109 is out of bounds for axis 0 with size 65
```

[38]:
```
topic_model.visualize_hierarchy(top_n_topics=n_results)
```

[39]:
```
topic_model.visualize_barchart(top_n_topics=n_results)
```

[39]:
```
# viz = list()
for topic in topic_mod:
  try:
    a, c = build_viz(topic, n_results)
    a.show()
    # b.show()
    c.show()
    # d.show()
  except ValueError:
    pass
```

```
# for i in d_topics:
#   i.visualize_topics()
```

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

5 Question 5 - Topic Summarization

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% (690/690), done.
remote: Compressing objects: 100% (192/192), done.
remote: Total 4385 (delta 598), reused 498 (delta 498), pack-reused 3695
Receiving objects: 100% (4385/4385), 9.84 MiB | 13.77 MiB/s, done.
Resolving deltas: 100% (2407/2407), done.
```

[38]:
```
%cd SummerTime/
# Pip install Summertime locally

# !pip install -e .
```

```
/content/SummerTime
```

[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-
jxaj27i9
  Running command git clone --filter=blob:none --quiet
https://github.com/bheinzerling/pyrouge.git /tmp/pip-req-build-jxaj27i9
  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=1f5b7119045475bd500d6c7418c0f2d37bc1c987c07be6d582b085f765c4f040
  Stored in directory: /tmp/pip-ephem-wheel-cache-
zxo05o1d/wheels/bd/07/80/f241050743bda1488efce41793a0b5502c97888adf191110d3
Successfully built pyrouge
Installing collected packages: pyrouge
Successfully installed pyrouge-0.1.3
```

[39]:

```
# 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
```

[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-4.27.2-py3-none-any.whl (6.8 MB)
Requirement already satisfied: filelock in /usr/local/lib/python3.9/dist-
packages (from transformers) (3.10.0)
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
MB)
Requirement already satisfied: pyyaml>=5.1 in /usr/local/lib/python3.9/dist-
packages (from transformers) (6.0)
Requirement already satisfied: numpy>=1.17 in /usr/local/lib/python3.9/dist-
packages (from transformers) (1.22.4)
Requirement already satisfied: regex!=2019.12.17 in
/usr/local/lib/python3.9/dist-packages (from transformers) (2022.10.31)
Requirement already satisfied: packaging>=20.0 in /usr/local/lib/python3.9/dist-
packages (from transformers) (23.0)
Collecting huggingface-hub<1.0,>=0.11.0
  Using cached huggingface_hub-0.13.3-py3-none-any.whl (199 kB)
Requirement already satisfied: requests in /usr/local/lib/python3.9/dist-
packages (from transformers) (2.27.1)
```

```
Requirement already satisfied: tqdm>=4.27 in /usr/local/lib/python3.9/dist-
packages (from transformers) (4.49.0)
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: charset-normalizer~=2.0.0 in
/usr/local/lib/python3.9/dist-packages (from requests->transformers) (2.0.12)
Requirement already satisfied: idna<4,>=2.5 in /usr/local/lib/python3.9/dist-
packages (from requests->transformers) (3.4)
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: certifi>=2017.4.17 in
/usr/local/lib/python3.9/dist-packages (from requests->transformers) (2022.12.7)
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.

summertime 1.2.1 requires transformers~=4.5.1, but you have transformers 4.27.2

which is incompatible.

datasets 1.6.2 requires huggingface-hub<0.1.0, but you have huggingface-hub

0.13.3 which is incompatible.

Successfully installed huggingface-hub-0.13.3 tokenizers-0.13.2
transformers-4.27.2
```

Implement Summarization

[36]:
```
def build_nir_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_nir(query, n_results=5):
  # Get the query embedding using the BERT-based model
  embedding = build_nir_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␣
 ↪similarity score
  indexes = np.argsort(similarity, axis=None)[::-1][:n_results]
```

```
  # Get the document IDs, texts, and similarity scores of the top n_results␣
↪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"] = "l"
  results.align["Similarity Score"] = "c"
  results.align["Text"] = "l"
  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)
```

Summarize the top 10 search results for each query in the query list

[40]:
```
from summertime import model

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:  The seller deals with you in the most professional way and
the security measures are superb. A great gift to your loved one and an ever
better seller.
Summary Review 2:  the only thing is that if the rings are not position
correctly it pinches the skin. i got this ring as a gift from my boyfriend and i
love it.
Summary Review 3:  It's a beautifull ring. I bought this as a gift for a friends
birthday and she loved it.
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 got this ring for my birthday and I love it, I cannot
imagine a woman not adoring this ring.
Summary Review 6:  I got this ring for my birthday and I love it, I cannot
imagine a woman not adoring this ring.
Summary Review 7:  I got this as my engagement ring Feb 09 This ring is
beautiful and durable. I absolutely love this ring!
Summary Review 8:  Just what I was looking for. It is so pretty and dainty.
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 diamonds are small and not very noticeable; I will be
sending this back This ring looks nothing like the picture.

QUERY 2 SUMMARIES
Summary Review 1:  Very disappointed in the appearance and quality of the
bracelet and its definitely not worth $45.00 - not even close.
Summary Review 2:  Just what I was looking for. It is so pretty and dainty.
Summary Review 3:  I got this ring for my birthday and I love it, I cannot
imagine a woman not adoring this ring.
```

Summary Review 4: I got this ring for my birthday and I love it, I cannot imagine a woman not adoring this ring.
Summary Review 5: It's a beautifull ring. I bought this as a gift for a friends birthday and she loved it.
Summary Review 6: The ring is pretty enough, but the metal of the ring is very insubstantial it pushes in very easily.
Summary Review 7: 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 8: The seller deals with you in the most professional way and the security measures are superb. A great gift to your loved one and an ever better seller.
Summary Review 9: I have always wanted a claddaugh ring.This price was great.I love it
Summary Review 10: :) :) I like it.

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 QUALITY IS SO MUCH MORE THAN I COULD HAVE EVER HOPED FOR. THIS ITEM WAS A WONDERFUL SURPRISE.
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: Recv'd my ring in a timely manner it looks very antique would recommend this ring to any garnet lover!
Summary Review 5: The seller deals with you in the most professional way and the security measures are superb. A great gift to your loved one and an ever better seller.
Summary Review 6: 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 7: The earrings were just as described the transaction was smooth and easy and the product was shipped and received in the time frame that was quoted I am very pleased with this purchase
Summary Review 8: I got this ring for my birthday and I love it, I cannot imagine a woman not adoring this ring.
Summary Review 9: I got this ring for my birthday and I love it, I cannot imagine a woman not adoring this ring.
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: great way to support the local pro sports team without wearing an oversized jersey or a hat to mess up the hair
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: The stones catch the light and the style is very comfortable to wear. It is so unique and a pleasure to wear.
Summary Review 8: I am looking forward to wearing them as they sparkle and catch every eye at my son's wedding on June 30
Summary Review 9: Just what I was looking for. It is so pretty and dainty.
Summary Review 10: 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.

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: The seller deals with you in the most professional way and the security measures are superb. A great gift to your loved one and an ever better seller.
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: It is too small for an adult. This is an attractive and high quality item for a young teenager.
Summary Review 5: THE QUALITY IS SO MUCH MORE THAN I COULD HAVE EVER HOPED FOR. THIS ITEM WAS A WONDERFUL SURPRISE.
Summary Review 6: I'm very happy with it and recommend it unreservedly. Item was great quality and came promptly.
Summary Review 7: Very flimsy.I would not recommend this item The quality and look were not what I had anticipated.
Summary Review 8: 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 9: It closes firmly with a clic and has a classic look. The look is very beautiful with a smooth finish.
Summary Review 10: i will not order from them again. the product arrived in perfect condition but the shipping is ridiculously slow.

QUERY 6 SUMMARIES
Summary Review 1: 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 2: 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 3: Really looks like the picture. Silver is nicely finished and the enamel is a nice highlight.
Summary Review 4: The color of the stones is rich and beautiful. The ring is exactly as pictured and looks very pretty on my hand.
Summary Review 5: They look like the picture. Just as described.
Summary Review 6: This medical alert braclet looked just like its picture and is nice quality sterling silver.

Summary Review 7: 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 8: CAN BE LAYED FOR A BEAUTIFUL LOOK. YET IT IS VERY PRETTY.
Summary Review 9: I really enjoy wearing something Celtic and pretty. The days I do not wear the blue one I wear this one.
Summary Review 10: It is an amazing price for such a beautiful pendant. It picks up the colors of your clothing.

QUERY 7 SUMMARIES
Summary Review 1: The ring was nice and looked like picture but had a crack in one Garnet and another one had a large chip.
Summary Review 2: The diamond had a crack in one Garnet and another one had a large chip.
Summary Review 3: 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 4: the diamonds are small and not very noticeable; I will be sending this back This ring looks nothing like the picture.
Summary Review 5: Although the picture looks like metal beads and description states sterling silver, these are pearls.
Summary Review 6: This works perfectly for my rings and my wider rings - both narrow and wide.
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: very nice small sized ring I can stack it with other rings for different looks
Summary Review 9: very nice small sized ring I can stack it with other rings for different looks
Summary Review 10: The ring is definitely NOT as advertised. Your picture of this rings shows blue sapphires so I was disappointed to see that the ring I received has such dark stones that they appear black.

QUERY 8 SUMMARIES
Summary Review 1: Really looks like the picture. Silver is nicely finished and the enamel is a nice highlight.
Summary Review 2: This medical alert braclet looked just like its picture and is nice quality sterling silver.
Summary Review 3: Although the picture looks like metal beads and description states sterling silver, these are pearls.
Summary Review 4: 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 5: They are more like silver plastic. I can't wear them with out completely bending the hooks out of shape.
Summary Review 6: It is an amazing price for such a beautiful pendant. It picks up the colors of your clothing.
Summary Review 7: They look like the picture. Just as described.

```
Summary Review 8:  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 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:  The ring is pretty but very flexible which turned out good
for me because I ordered for my ring finger and the size of it made it look
better as a pinkie ring.
```

[48]:
```python
# Fetch the top values to be inputed in ChatGPT to determine target
_values = list()
_summaries = list()

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

print('\n')

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

```
1 - The seller deals with you in the most professional way and the security
measures are superb. A great gift to your loved one and an ever better seller.
2 - Very disappointed in the appearance and quality of the bracelet and its
definitely not worth $45.00 - not even close.
3 - I'm very happy with it and recommend it unreservedly. Item was great quality
and came promptly.
4 - very good for everyday wear or dressing up
5 - 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.
6 - 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.
7 - The ring was nice and looked like picture but had a crack in one Garnet and
another one had a large chip.
8 - Really looks like the picture. Silver is nicely finished and the enamel is a
nice highlight.


1 - 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.
2 - Very disappointed in the appearance and quality of the bracelet and its
definitely not worth $45.00 - not even close.
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 earrings are as in the picture, stones look good and are light and
comfortable, reasonable quality for the price. The silver does not look as in
the picture but just like polished silver.
7 - The ring was nice and looked like picture but had a crack in one Garnet and
another one had a large chip.
8 - 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.
```

Evaluation of Summarization

[42]:
```python
!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.
 ↪',
    'High-quality item arrived quickly. Extremely satisfied and wholeheartedly␣
 ↪recommend.',
    'Suitable and fashionable for dressy occasions.',
    'Received nice product earlier than expected. Will reorder.',
    'Colorful turtle items resembling the photograph. Comparable to expensive␣
 ↪ones, and beautiful.',
    'Ring appears smaller than pictured with very small diamonds, causing␣
 ↪disappointment.',
    'Medical alert bracelet matches picture and is made of quality sterling␣
 ↪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
```

```python
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.bias',
'cls.seq_relationship.bias', 'cls.predictions.transform.LayerNorm.weight',
'cls.predictions.bias', 'cls.predictions.transform.LayerNorm.bias',
'cls.predictions.decoder.weight', 'cls.predictions.transform.dense.weight',
'cls.seq_relationship.weight']
- 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…
[nltk_data]   Package wordnet is already up-to-date!
```

```
hash_code: bert-base-uncased_L8_no-idf_version=0.3.12(hug_trans=4.27.2)
BertScore: {'bert_score_f1': 0.5041931867599487}
Meteor: {'meteor': 0.05602394087791603}
BLEU: {'bleu': 0.004187602191129517}
+-----------+-----------+
| Metric    |     Score |
+===========+===========+
| BertScore | 0.504193  |
+-----------+-----------+
| Meteor    | 0.0560239 |
+-----------+-----------+
| BLEU      | 0.0041876 |
+-----------+-----------+
```

Summarize evaluation anwer - TODO

5b - Interactive summarization

[ ]:
```python
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')


  sentence_summary = ["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.",
```

```
"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."]
```

```
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."]
```

[ ]:
```
no_sentences = input("Enter number of sentences you desire to be summarized: ")
user_summaries = []
summary_list = []
for i in range(int(no_sentences)):
    list_val = input(f"Enter sentence {i+1}: \n")
    user_summaries.append(list_val)
    # user_summaries.append([list_val]))

for i, val in enumerate(user_summaries):
  lexrank = model.LexRankModel(user_summaries)
  # Inference
  summary = lexrank.summarize([user_summaries[i]])
  summary_list.append(summary)
```

```
    print(f"="*200)
    print(f"\nSummary for Sentence {i+1}")
    print(f"Summarized Sentence {i+1} - {user_summaries[i]}")
    print(f"Summary {i+1} - {summary[0]}")
    print('\n')
```

```
Enter number of sentences you desire to be summarized: 2
Enter sentence 1:
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.
Enter sentence 2:
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.
================================================================================
================================================================================
========================================

Summary for Sentence 1
Summarized Sentence 1 - 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 1 - 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.


================================================================================
================================================================================
========================================

Summary for Sentence 2
Summarized Sentence 2 - 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.
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.
```

[ ]:
```python
no_sentences = input("Enter number of sentences you desire to be summarized: ")
max_words = int(input("Enter maximum number of words for the summary: "))
user_summaries = []
summary_list = []
for i in range(int(no_sentences)):
    list_val = input(f"Enter sentence {i+1}: \n")
    user_summaries.append(list_val)

for i, val in enumerate(user_summaries):
    lexrank = model.LexRankModel(user_summaries)
    # Inference
    summary = lexrank.summarize([user_summaries[i]])
    # Split summary into words and join only the desired number of words
    summary_words = summary[0].split()[:max_words]
    summary = ' '.join(summary_words)
    summary_list.append(summary)
    print('\n')
    print(f"Summary for Sentence {i+1}")
    print(f"Summarized Sentence {i+1} - {user_summaries[i]}")
    print(f"Summary {i+1} - {summary}")
    print('\n')
```

```
Enter number of sentences you desire to be summarized: 2
Enter maximum number of words for the summary: 20
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
Summarized 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.
Summary 1 - The club's first game was against Eastern Wanderers and ended in a
6-0 victory for Dial Square. Arsenal was founded




Summary for Sentence 2
```

```
Summarized 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 2 - The club's most successful period came under the management of
Arsene Wenger, who led the team to three Premier League
```

[ ]:
```
!sudo apt-get install texlive-xetex texlive-fonts-recommended␣
↪texlive-plain-generic
```

[ ]:
```
# %%shell
!jupyter nbconvert --to pdf '/content/drive/My Drive/Colab Notebooks/COP509cw/
↪F218341_NLPCoursework.ipynb'
```

[ ]:
```

```