DMT2023_HW1

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0.1 Group composition:

————YOUR TEXT STARTS HERE————

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0.2 Homework 1

The homework consists of two parts:

1. Search-Engine Evaluation

and

2. Near-Duplicate-Detection

1 Part 1

In this part of the homework, you have to index collections of documents to build search-engines using the PyTerrier library.

Import **ALL** the Python packages that you need for Part 1.

[ ]:
```
#REMOVE_OUTPUT#
!pip install --upgrade --no-cache-dir gdown
from bs4 import BeautifulSoup
#YOUR CODE STARTS HERE#
!pip install python-terrier
import pyterrier as pt
import pandas as pd
if not pt.started():
  pt.init()
import matplotlib.pyplot as plt
import warnings
warnings.filterwarnings("ignore", category=DeprecationWarning)
warnings.simplefilter(action='ignore', category=pd.errors.PerformanceWarning)
#YOUR CODE ENDS HERE#
#THIS IS LINE 15#
```

1.1 Part 1.1

You have to build a search engine for the book *Le Morte D'Arthur* by Thomas Malory and **improve the search-engines performance** (the higher the better). The book is divided into two volumes. Each chapter is a document with two fields: title of the chapter and corpus of the chapter. You only want to index the corpus of each chapter.

1.1.1 1.1.1

Download the data from the Drive link (code already provided).

[ ]:
```
#REMOVE_OUTPUT#
!gdown 1zHgvidy9FvhZvE68SOmXWkoF-hHMpiUL
!gdown 1VjpTkFcbfaLIi4TXVafokW9e_bvGnfut
```

1.1.2 1.1.2

Parse the HTML. **Part** of code already provided: follow the comments to complete the code.

[285]:
```python
with open('The Project Gutenberg eBook of Le Morte D'Arthur, Volume I (of II),␣
↪by Thomas Malory.html') as fp:
    vol1 = BeautifulSoup(fp, 'html.parser')
with open('The Project Gutenberg eBook of Le Morte D'Arthur, Volume II (of II),␣
↪by Thomas Malory.html') as fp:
    vol2 = BeautifulSoup(fp, 'html.parser')

def clean_text(txt):
    words_to_put_space_before = [".",",",";",":","'","'"]
    words_to_lowercase =␣
↪["First","How","Some","Yet","Of","A","The","What","Fifth"]

    app = txt.replace("\n"," ")
    for word in words_to_put_space_before:
        app = app.replace(word," "+word)
    for word in words_to_lowercase:
        app = app.replace(word+" ",word.lower()+" ")
    return app.strip()

def parse_html(soup):
    titles = []
    texts = []
    for chapter in soup.find_all("h3"):
        chapter_title = chapter.text
        if "CHAPTER" in chapter_title:
            chapter_title = clean_text("".join(chapter_title.split(".")[1:]))
            titles.append(chapter_title)

            chapter_text = [p.text for p in chapter.findNextSiblings("p")]
            chapter_text = clean_text(" ".join(chapter_text))
            texts.append(chapter_text)
    return titles, texts
```

[286]:
```python
#YOUR CODE STARTS HERE#
#Extract all the chapters' titles and texts from the two volumes
vol1_titles, vol1_texts = parse_html(vol1)
vol2_titles, vol2_texts = parse_html(vol2)









#Transform the list into a pandas DataFrame (a PyTerrier friendly structure).
d1 = {'title' : vol1_titles, 'text' : vol1_texts, 'vol_nr' : [1 for _ in␣
↪range(len(vol1_titles))]}
df_vol1 = pd.DataFrame(d1)
```

```
d2 = {'title' : vol2_titles, 'text' : vol2_texts, 'vol_nr' : [2 for _ in␣
↪range(len(vol2_titles))]}
df_vol2 = pd.DataFrame(d2)

df_book = pd.concat([df_vol1, df_vol2], ignore_index = True)
df_book['docno'] = [str(i) for i in range(len(df_book))]
#YOUR CODE ENDS HERE#
#THIS IS LINE 20#
```

[287]:
```
#YOUR CODE STARTS HERE#
print("The first 8 rows of DataFrame 'df_book':")
df_book.head(8)






#YOUR CODE ENDS HERE#
#THIS IS LINE 10#
```

```
The first 8 rows of DataFrame 'df_book':
```

[287]:
```
                                               title  \
0  first , how Uther Pendragon sent for the duke …
1  how Uther Pendragon made war on the duke of Co…
2     of the birth of King Arthur and of his nurture
3               of the death of King Uther Pendragon
4  how Arthur was chosen king , and of wonders an…
5  how King Arthur pulled out the sword divers times
6  how King Arthur was crowned , and how he made …
7  how King Arthur held in Wales , at a Pentecost…

                                                text  vol_nr docno
0  It befell in the days of Uther Pendragon , whe…       1     0
1  Then Ulfius was glad , and rode on more than a…       1     1
2  Then Queen Igraine waxed daily greater and gre…       1     2
3  Then within two years King Uther fell sick of …       1     3
4  Then stood the realm in great jeopardy long wh…       1     4
5  Now assay , said Sir Ector unto Sir Kay . And …       1     5
6  And at the feast of Pentecost all manner of me…       1     6
7  Then the king removed into Wales , and let cry…       1     7
```

1.1.3 1.1.3

Extract character's names from the **titles** only. **Part** of code already provided: follow the comments to complete the code.

[288]:
```
all_characters = set()
def extract_character_names_from_string(string_to_parse):
    special_tokens = ["of","the","le","a","de"]

    remember = ""
    last_is_special_token = False

    tokens = string_to_parse.split(" ")
    characters_found = set()
    for i,word in enumerate(tokens):
        if word[0].isupper() or (remember!="" and word in special_tokens):
            #word = word.replace("'s","").replace("’s","")
            last_is_special_token = False
            if remember!="":
                if word in special_tokens:
                    last_is_special_token = True
                remember = remember+" "+word
            else: remember = word
        else:
            if remember!="":
                if last_is_special_token:
                    for tok in special_tokens:
                        remember = remember.replace(" "+tok,"")
                characters_found.add(remember)
            remember = ""
            last_is_special_token = False
    return characters_found

#all_characters = set([x for x in all_characters if x[-2:]!="'s"])
```

[289]:
```
#YOUR CODE STARTS HERE#
#Extract all characters' names
for title in df_book['title']:
  all_characters.update(extract_character_names_from_string(title))
```

```
#YOUR CODE ENDS HERE#
#THIS IS LINE 15#
```

[290]:
```
#YOUR CODE STARTS HERE#
kings = [name for name in all_characters if 'king' in name.lower()]
kings = list(set(kings)) # to remove duplicates
print("The names of all kings in the book: \n")
kings




#YOUR CODE ENDS HERE#
#THIS IS LINE 10#
```

```
The names of all kings in the book:

```

[290]:
```
['King Anguish of Ireland',
 'King of the Land of Cameliard',
 'King Rience',
 'King Ban',
 'King Arthur',
 'King of England',
 'King Howel of Brittany',
 'King Mark',
 'King Pellinore',
 'King Mordrains',
 'King Leodegrance',
 'Maimed King',
 'King Pellam',
 'King Brandegore',
 'King Lot',
 'King Bagdemagus',
 'King Pelles',
 'King Lot of Orkney',
 'King Pelleas',
 'King',
 'King Mark of Cornwall',
 'King Evelake',
 'King Uriens',
 'King Solomon',
 'King Bors']
```

1.1.4 1.1.4

Some names refer to the same characters (e.g. `'Arthur' = 'King Arthur'`). A function is provided to extract the disambiguation dictionary: each key represents a name and the value represents the true character name (e.g. `{'Arthur': 'King-Arthur', 'King': 'King-Arthur', 'Bedivere':'Sir Bedivere'}`). Disambiguation sets, i.e. a list with sets representing the multiple names of a single character, are also provided.

> There may be some mistakes, but it does not matter (e.g. `'Cornwall' = 'King of Cornwall'`)

[291]:
```python
disambiguate_to = {}
for x in all_characters:
    for y in all_characters:
        if x in y and x!=y:
            if x in disambiguate_to:
                previous_y = disambiguate_to[x]
                if len(y)>len(previous_y): disambiguate_to[x] = y
            else:
                disambiguate_to[x] = y
disambiguate_to.update({"King": "King Arthur",
                        "King of England": "King Arthur",
                        "Queen": "Queen Guenever",
                        "Sir Lancelot": "Sir Launcelot"})

disambiguate_sets = []
for x,y in disambiguate_to.items():
    inserted = False
    for z in disambiguate_sets:
        if x in z or y in z:
            z.add(x); z.add(y)
            inserted = True
    if not inserted:
        disambiguate_sets.append(set([x,y]))

while True:
    to_remove,to_add = [],[]
    for i1,s1 in enumerate(disambiguate_sets[:-1]):
        for s2 in disambiguate_sets[i1+1:]:
            if len(s1.intersection(s2))>0:
                to_remove.append(s1)
                to_remove.append(s2)
                to_add.append(s1.union(s2))
    if len(to_add)>0:
        for rm in to_remove:
            disambiguate_sets.remove(rm)
        for ad in to_add:
            disambiguate_sets.append(ad)
```

```
    else: break
```

[292]:
```
#YOUR CODE STARTS HERE#
sets_of_topics = disambiguate_sets.copy()
for sets in disambiguate_sets:
  for alternative_name in sets:
    if alternative_name in all_characters:
        all_characters.remove(alternative_name)

for char in all_characters:
  sets_of_topics.append({char})

topics = [', '.join(s) for s in sets_of_topics] # we use the comma to be then␣
 ↪able to split the alternative names
dic_of_topics = { 'qid' : [str(i) for i in range(len(topics))], 'query': topics}
df_topics = pd.DataFrame(dic_of_topics)


















#YOUR CODE ENDS HERE#
#THIS IS LINE 30#
```

[293]:
```
#YOUR CODE STARTS HERE#
print("The first 5 rows of DataFrame 'df_topics':")
df_topics.head(5)






#YOUR CODE ENDS HERE#
#THIS IS LINE 10#
```

```
The first 5 rows of DataFrame 'df_topics':
```

[293]:

	qid	query
0	0	Holy Sangreal, Sangreal
1	1	Sir Tristram de Liones, Sir Tristram, Tristram
2	2	Joyous Gard, Gard
3	3	Queen, Queen Guenever, Guenever
4	4	Round Table, Knights of the Round Table

1.1.5 1.1.6

Prepare the relevance scores for the queries.

> A document is considered relevant (1) if its **corpus** contains the character's name or one of its alternative names, otherwise is not relevant (0).

[294]:
```python
#YOUR CODE STARTS HERE#
d = {'qid': [], 'docno' : [], 'label' : []}
label = 0
for row1 in df_topics.iterrows():
  for row2 in df_book.iterrows():
    d['qid'].append(str(row1[1][0]))
    d['docno'].append(str(row2[1][3]))
    for name in row1[1][1].split(','):
       # 'King' and 'Queen' are not valid names to determine relevance in a document because they are not unique
      if name in row2[1][1] and name not in ['King', 'Queen']:
        label = 1
        break
      else:
        label = 0
    d['label'].append(label)

qrels = pd.DataFrame(d)











#YOUR CODE ENDS HERE#
#THIS IS LINE 30#
```

[295]:
```python
#YOUR CODE STARTS HERE#
print("The first row of the DataFrame 'qrels':")
display(qrels.head(1))
print(" ")
print("The last row of the DataFrame 'qrels':")
display(qrels.tail(1))
print(" ")
print("The shape of the DataFrame 'qrels' is: ", qrels.shape)
#YOUR CODE ENDS HERE#
```

```
#THIS IS LINE 10#
```

```
The first row of the DataFrame 'qrels':

  qid docno  label
0   0     0      0


The last row of the DataFrame 'qrels':

       qid docno  label
85509  169   502      0


The shape of the DataFrame 'qrels' is:  (85510, 3)
```

1.1.6 1.1.7

Choose several preprocessing configurations (at least 2, no more than 4).

For each of them, construct an index on the `title` field.

For the last of them, report the number of indexed documents and terms.

[296]:
```
#YOUR CODE STARTS HERE#
configurations = ["",
                  "Stopwords",
                  "PorterStemmer",
                  "Stopwords, EnglishSnowballStemmer"]

def create_index(configuration, field):
  pd_indexer = pt.DFIndexer("./Inverted_Index", overwrite=True)
  pd_indexer.setProperty("termpipelines", configuration)
  indexref = pd_indexer.index(df_book[field], df_book["docno"])
  return indexref

indexref = create_index(configurations[-1], "title")
index = pt.IndexFactory.of(indexref)
print("The number of indexed documents and terms for the configuration␣
 ↪'Stopwords, EnglishSnowballStemmer': \n")
print(index.getCollectionStatistics().toString())


#YOUR CODE ENDS HERE#
#THIS IS LINE 20#
```

```
The number of indexed documents and terms for the configuration 'Stopwords,
EnglishSnowballStemmer':

Number of documents: 503
Number of terms: 807
Number of postings: 4209
Number of fields: 0
Number of tokens: 4655
Field names: []
Positions:   false
```

1.1.7 1.1.8

Choose several weighting models (at least 2, no more than 5).

For each of them, for each of the indices created in last step, build a retrieval model.

[297]:
```
#YOUR CODE STARTS HERE#
possible_wmodels = ["CoordinateMatch",
                    "TF_IDF",
                    "BM25",
                    "PL2",
                    "LemurTF_IDF"]

def create_retrieval_model(indexref, scoring_function):
  return pt.BatchRetrieve(indexref, wmodel = scoring_function)

list_of_retrieval_models = []
for configuration in configurations:
  indexref = create_index(configuration, "title")
  for wmodel in possible_wmodels:
    retrieval_model = create_retrieval_model(indexref, wmodel)
    list_of_retrieval_models.append(retrieval_model)


#YOUR CODE ENDS HERE#
#THIS IS LINE 20#
```

1.1.8 1.1.9

Choose several evaluation metrics (at least 3, no more than 6) and put them in a list.

Add the following metrics to the list: Recall at 5, Normalized Discounted Cumulative Gain at 20, Mean Average Precision.

Obviously, the metrics you choose cannot be **completely identical** to these 3 we specified.

[298]:
```
#YOUR CODE STARTS HERE#
eval_metrics = ["P_5",
                "P_10",
                "Rprec",
                "recall_20",
                "ndcg_cut_10",
                "num_rel",
                "recall_5",
                "ndcg_cut_20",
                "map"]
```

```
#YOUR CODE ENDS HERE#
#THIS IS LINE 20#
```

1.1.9 1.1.10

For each index built in step 1.1.7, run an experiment to obtain the values associated to each evaluation metrics specified in 1.1.8 for each of the weighting models chosen in 1.1.9.

[299]:
```
#YOUR CODE STARTS HERE#
result = pt.Experiment(
    list_of_retrieval_models,
    df_topics,
    qrels,
    eval_metrics,
    highlight="bold",
    names = ["CoordinateMatch_without_preprocessing",␣
 ↪"TF_IDF_without_preprocessing", "BM25_without_preprocessing",
             "PL2_without_preprocessing", "LemurTF_IDF_without_preprocessing",␣
 ↪"CoordinateMatch_with_stopwords",
             "TF_IDF_with_stopwords", "BM25_with_stopwords",␣
 ↪"PL2_with_stopwords", "LemurTF_IDF_with_stopwords",
             "CoordinateMatch_with_PorterStemmer", "TF_IDF_with_PorterStemmer",␣
 ↪"BM25_with_PorterStemmer",
             "PL2_with_PorterStemmer", "LemurTF_IDF_with_PorterStemmer",
             "CoordinateMatch_with_stopwords_and_EnglishSnowballStemmer",␣
 ↪"TF_IDF_with_stopwords_and_EnglishSnowballStemmer",
             "BM25_with_stopwords_and_EnglishSnowballStemmer",␣
 ↪"PL2_with_stopwords_and_EnglishSnowballStemmer",
             "LemurTF_IDF_with_stopwords_and_EnglishSnowballStemmer"]
)











#YOUR CODE ENDS HERE#
```

```
#THIS IS LINE 30#
```

1.1.10 1.1.11

For the last index constructed (i.e. corresponding to the last preprocessing chosen), print out the PyTerrier table with the weighting models chosen by you on the rows and the evaluation metrics chosen by you + those specified by us on the columns.

Highlight the best results in the result table.

[300]:
```
#YOUR CODE STARTS HERE#
display(result.data)
best_results = {}
for metric in eval_metrics:
  name = list(result.data['name'][result.data[metric] == result.data[metric].
 ↪max()])
  best_results[metric] = (name, max)
print("\n The best results for each metric: \n") # to fix the PDF display␣
 ↪problem with Styler Object
best_results
#YOUR CODE ENDS HERE#
#THIS IS LINE 10#
```

```
                                               name       P_5      P_10  \
0                 CoordinateMatch_without_preprocessing  0.436471  0.295882
1                          TF_IDF_without_preprocessing  0.454118  0.311176
2                            BM25_without_preprocessing  0.442353  0.310000
3                             PL2_without_preprocessing  0.456471  0.309412
4                      LemurTF_IDF_without_preprocessing  0.445882  0.310000
5                          CoordinateMatch_with_stopwords  0.437647  0.293529
6                                 TF_IDF_with_stopwords  0.448235  0.310000
7                                   BM25_with_stopwords  0.444706  0.312353
8                                    PL2_with_stopwords  0.448235  0.308824
9                            LemurTF_IDF_with_stopwords  0.447059  0.310588
10                   CoordinateMatch_with_PorterStemmer  0.437647  0.295294
11                            TF_IDF_with_PorterStemmer  0.455294  0.311765
12                              BM25_with_PorterStemmer  0.444706  0.311765
13                               PL2_with_PorterStemmer  0.457647  0.311176
14                       LemurTF_IDF_with_PorterStemmer  0.447059  0.311765
15  CoordinateMatch_with_stopwords_and_EnglishSnow…  0.440000  0.294706
16   TF_IDF_with_stopwords_and_EnglishSnowballStemmer  0.450588  0.311765
17     BM25_with_stopwords_and_EnglishSnowballStemmer  0.447059  0.314118
18      PL2_with_stopwords_and_EnglishSnowballStemmer  0.450588  0.310588
19  LemurTF_IDF_with_stopwords_and_EnglishSnowball…  0.449412  0.312353

       Rprec  recall_20  ndcg_cut_10  num_rel  recall_5  ndcg_cut_20       map
0   0.285711   0.266166     0.496643   4107.0  0.227657     0.445407  0.291373
1   0.299906   0.279550     0.509788   4107.0  0.236765     0.461265  0.302762
```

2	0.296988	0.278635	0.507098	4107.0	0.233625	0.458322	0.299754
3	0.298966	0.279213	0.507716	4107.0	0.236915	0.459609	0.300517
4	0.299685	0.279226	0.507138	4107.0	0.234272	0.458724	0.300959
5	0.281658	0.263475	0.494228	4107.0	0.227477	0.443942	0.286416
6	0.295166	0.276049	0.509010	4107.0	0.235381	0.459486	0.297617
7	0.293500	0.278215	0.510223	4107.0	0.232824	0.460399	0.296200
8	0.295279	0.275992	0.507246	4107.0	0.235381	0.458247	0.296103
9	0.295250	0.275950	0.507986	4107.0	0.234975	0.458056	0.296795
10	0.286480	0.266693	0.496258	4108.0	0.227902	0.445555	0.291529
11	0.300922	0.281469	0.510488	4108.0	0.236626	0.462678	0.303831
12	0.299037	0.280563	0.508870	4108.0	0.233938	0.460496	0.301079
13	0.300289	0.281316	0.509241	4108.0	0.236775	0.460924	0.301700
14	0.301929	0.282122	0.508566	4108.0	0.234517	0.460733	0.302388
15	0.282058	0.264108	0.494980	4108.0	0.227790	0.444123	0.287350
16	0.297732	0.279486	0.510501	4108.0	0.235694	0.462180	0.299355
17	0.296066	0.281651	0.511666	4108.0	0.233136	0.463062	0.297959
18	0.297845	0.279369	0.508737	4108.0	0.235694	0.460736	0.297812
19	0.297815	0.279386	0.509170	4108.0	0.235288	0.460552	0.298395

```
The best results for each metric:
```

[300]:
```
{'P_5': (['PL2_with_PorterStemmer'], 0.30383095919100905),
 'P_10': (['BM25_with_stopwords_and_EnglishSnowballStemmer'],
  0.30383095919100905),
 'Rprec': (['LemurTF_IDF_with_PorterStemmer'], 0.30383095919100905),
 'recall_20': (['LemurTF_IDF_with_PorterStemmer'], 0.30383095919100905),
 'ndcg_cut_10': (['BM25_with_stopwords_and_EnglishSnowballStemmer'],
  0.30383095919100905),
 'num_rel': (['CoordinateMatch_with_PorterStemmer',
   'TF_IDF_with_PorterStemmer',
   'BM25_with_PorterStemmer',
   'PL2_with_PorterStemmer',
   'LemurTF_IDF_with_PorterStemmer',
   'CoordinateMatch_with_stopwords_and_EnglishSnowballStemmer',
   'TF_IDF_with_stopwords_and_EnglishSnowballStemmer',
   'BM25_with_stopwords_and_EnglishSnowballStemmer',
   'PL2_with_stopwords_and_EnglishSnowballStemmer',
   'LemurTF_IDF_with_stopwords_and_EnglishSnowballStemmer'],
  0.30383095919100905),
 'recall_5': (['PL2_without_preprocessing'], 0.30383095919100905),
 'ndcg_cut_20': (['BM25_with_stopwords_and_EnglishSnowballStemmer'],
  0.30383095919100905),
 'map': (['TF_IDF_with_PorterStemmer'], 0.30383095919100905)}
```

1.1.11 1.1.12

Select the Top-4 configurations (preprocessing, weighting model) according to the Mean Average Precision (MAP), taking into account the results obtained in section 1.1.10.

For these 4 configurations, provide the following plot (re-run the evaluations just for this configurations, to get the required evaluation metrics):

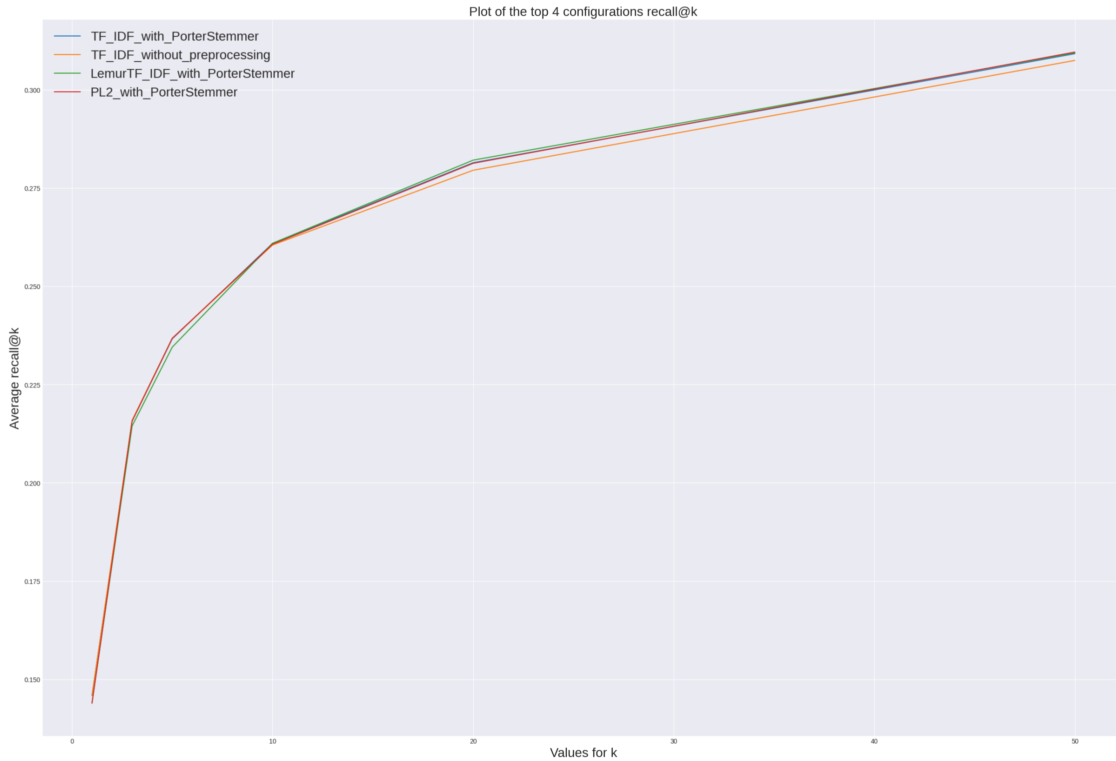
- Recall@k plot
  - the x axis represents the considered values for k: you must consider k {1, 3, 5, 10, 20, 50}
  - the y axis represents the average Recall@k over all provided queries
  - each curve represents one of the 4 search engine configurations

[301]:

```
#YOUR CODE STARTS HERE#
index_top_4 = result.data.nlargest(4, ['map']).index
top_4_configurations = [list_of_retrieval_models[i] for i in index_top_4]
new_eval_metrics = ["recall_1", "recall_3", "recall_5", "recall_10",␣
 ↪"recall_20", "recall_50"]

result2 = pt.Experiment(
    top_4_configurations,
    df_topics,
    qrels,
    new_eval_metrics,
    highlight="bold",
    names = result.data['name'].loc[index_top_4]
)

print("Pyterrier table:")
display(result2.data)
print(" ")

plt.style.use("seaborn-darkgrid")
fig,ax = plt.subplots(figsize=(30, 20))
for i in range(4):
  d = {1 : result2.data["recall_1"][i], 3: result2.data["recall_3"][i],
      5 : result2.data["recall_5"][i], 10 : result2.data["recall_10"][i],
      20: result2.data["recall_20"][i], 50 : result2.data["recall_50"][i]}

  ax.plot(d.keys(), d.values(), )
  ax.set_xlabel('Values for k', fontsize = 20)
  ax.set_ylabel('Average recall@k', fontsize = 20)
  ax.legend(result.data['name'].loc[index_top_4], prop={'size': 20})

plt.title("Plot of the top 4 configurations recall@k", fontsize = 20)
plt.show()
```

```
#YOUR CODE ENDS HERE#
#THIS IS LINE 50#
```

```
Pyterrier table:
                               name  recall_1  recall_3  recall_5  recall_10  \
0        TF_IDF_with_PorterStemmer  0.145819  0.215707  0.236626   0.260927
1     TF_IDF_without_preprocessing  0.145819  0.215915  0.236765   0.260505
2   LemurTF_IDF_with_PorterStemmer  0.144005  0.214460  0.234517   0.260963
3           PL2_with_PorterStemmer  0.143858  0.215707  0.236775   0.260709

   recall_20  recall_50
0   0.281469   0.309223
1   0.279550   0.307510
2   0.282122   0.309457
3   0.281316   0.309640
```


Plot of the top 4 configurations recall@k
TF_IDF_with_PorterStemmer
TF_IDF_without_preprocessing
LemurTF_IDF_with_PorterStemmer
PL2_with_PorterStemmer
0.300
0.275
0.250
0.225
0.200
0.175
0.150
Average recall@k
0
10
20
30
40
50
Values for k

1.1.12 1.1.13

According only to the Recall@k plot, which is the best search engine configuration? Explain your answer in **at most 3 sentences**.

————YOUR TEXT STARTS HERE————

All the four configurations show similar results in the plot, so they all turn out to be good options for the search engine configuration in our dataset.

In general, **green and red curve** (respectively *LemurTF_IDF_with_PorterStemmer* and *PL2_with_PorterStemmer*) seem to us to be more robust when we are dealing with more data and the plot turns out that **no pre-processing leads to worse results increasing k**.

Between the two configurations, we decide to choose the one where we use **PorterStemmer** for the pre-processing and the **PL2** retrieval model, but we argue that LemurTF_IDF and TF_IDF models are probably also a valid choice.

1.1.13 1.1.14

For the configuration you selected in Part 1.1.13, provide an **example of the functioning** of your search enginge.

The query should be `King Mark of Cornwall`.

[302]:
```
#YOUR CODE STARTS HERE#
query = "King Mark of Cornwall"
search_engine = pt.BatchRetrieve(create_index("PorterStemmer", "title"),␣
 ↪wmodel="PL2").search(query)
print("Search engine results:")
display(search_engine)

print("\n")
print("Print of the top 3 search engine results in the Dataframe df_book: \n")
top_3_docid = list(search_engine['docid'])[:3]
for docid in top_3_docid:
  print(df_book.loc[docid], "\n")









#YOUR CODE ENDS HERE#
#THIS IS LINE 20#
```

```
Search engine results:

    qid  docid docno  rank     score                  query
0     1    231   231     0  6.673539  King Mark of Cornwall
1     1    215   215     1  6.622714  King Mark of Cornwall
2     1    259   259     2  6.295796  King Mark of Cornwall
3     1     33    33     3  5.819559  King Mark of Cornwall
4     1    252   252     4  4.942725  King Mark of Cornwall
..   ..    …     …    …        …                      …
328   1    360   360   328  0.640278  King Mark of Cornwall
329   1    137   137   329  0.637367  King Mark of Cornwall
330   1    417   417   330  0.637367  King Mark of Cornwall
331   1    135   135   331  0.627802  King Mark of Cornwall
332   1    133   133   332  0.625822  King Mark of Cornwall

[333 rows x 6 columns]



Print of the top 3 search engine results in the Dataframe df_book:
```

```
title     how King Mark was sorry for the good renown of…
text      Now will we speak , and leave Sir Tristram , S…
vol_nr                                                  1
docno                                                 231
Name: 231, dtype: object

title     how King Mark , by the advice of his council ,…
text      Then the queen departed , but the brachet woul…
vol_nr                                                  1
docno                                                 215
Name: 215, dtype: object

title     how King Arthur made King Mark to be accorded …
text      Now pass we our matter , and leave we Sir Gawa…
vol_nr                                                  2
docno                                                 259
Name: 259, dtype: object
```

1.2 Part 1.2

1.2.1 1.2.1

Scenario: The company ExcaliburDMT needs a search engine for the book *Le Morte D'Arthur* by Thomas Malory. The book is divided into two volumes.

> They want to consider each chapter as a document with two fields: title of the chapter and corpus of the chapter. For now, they only want to index the title of each chapter.
>
> They only want their users to be able to query character names and match them exactly (also, order is important).
>
> They would like to show 10 results on the screen in a random order, in a sword-like shape.
>
> The company wants to evaluate the performance of the search engine: each chapter's title containing a character's name is considered relevant for a query containing that character's name.

Character names are extracted from the collection of documents. See Part 1.1.3.

Order is important: if the query is "King Arthur", "Arthur, King of Britain" should have less scoring than "King Arthur of Camelot".

What is the configuration (as defined in part 1.2) that would best meet the needs of the Excalibur-DMT company? **Use at most 3 sentences (1 per section).**

————YOUR TEXT STARTS HERE————

Preprocessing: Clean Text + Tokenization

Weighting model: PL2 + 1 extra point in the score if there's a phrase match

Evaluation metric: Recall_10

Provide an explanation of your choice in **at most 3 sentences**.

————YOUR TEXT STARTS HERE————

To respond to this new need, we can clean and pre-process query and the document titles as a list of **ordered tokens** using Tokenization.

Once pre-processed, we can use **PL2** as retrieval model with the addition of **1 extra point** to the final score if there is a **phrase match** between the query and a part of the document: that means, if the character is indicated in the title of the document with the same order of the query will be *pushed up* in the score table.

Finally, we can evaluate our search engine with **Recall_10** displaying this top 10 results in a random order.

2 Part 2

[ ]:
```
#REMOVE_OUTPUT#
#YOUR CODE STARTS HERE#
import csv
import random
import itertools as it
import numpy as np
import pandas as pd
import time
import matplotlib.pyplot as plt




#YOUR CODE ENDS HERE#
#THIS IS LINE 15#
```

[304]:
```
set__characters_of_interest = set(
    [' ', '0', '1', '2', '3', '4', '5', '6', '7', '8', '9', 'a', 'b', 'c', 'd',␣
 ↪'e', 'f', 'g', 'h', 'i', 'j', 'k', 'l',
     'm', 'n', 'o', 'p', 'q', 'r', 's', 't', 'u', 'v', 'w', 'x', 'y', 'z'])
def cleaner(text, set__characters_of_interest):
    new_text = ""
    #
    previous_copied_character = "a"
    for c_character in text:
        #
        c_character = c_character.lower()
        #
        if c_character not in set__characters_of_interest:
            c_character = " "
        #
        if c_character == " " and c_character == previous_copied_character:
            continue
        #
        new_text += c_character
        #
        previous_copied_character = c_character
        #
    #
    new_text = new_text.strip()
    #
    return new_text
```

[305]:
```
def get_shingle_id(shingle):
    global max_shingle_id
```

```
    global map__shingle__shingle_id
    #
    shingle_id = map__shingle__shingle_id.get(shingle, -1)
    #
    if shingle_id >= 0:
        return shingle_id

    max_shingle_id += 1
    shingle_id = max_shingle_id
    map__shingle__shingle_id[shingle] = max_shingle_id
    #
    return shingle_id
```

[306]:
```
def shingler(text, width=2):
    #
    set__shingle_id = set()
    #
    tokenized_text = text.split(" ")
    #
    max_index_plus_1 = 1 if len(tokenized_text) <= width else␣
 ↪len(tokenized_text) - width +1
    for index in range(max_index_plus_1):
        #
        c_shingle = tuple(tokenized_text[index:index + width])
        #
        shingle_id = get_shingle_id(c_shingle)
        #
        # if shingle_id in set__shingle_id:
        #     print(shingle_id, c_shingle)
        #
        res = set__shingle_id.add(shingle_id)
        #
    return set__shingle_id
```

[307]:
```
def create_sets_of_shingle_ids(input_file_name, output_file_name,
                               input_file_delimiter='\t',␣
 ↪input_file_quotechar='"',
                               set__characters_of_interest=[" "],␣
 ↪shingle_width=3,
                               doc_id_column_idx=0, field_column_idx=1):
    #
    output_file = open(output_file_name, 'w', encoding="utf-8")
    output_file_csv_writer = csv.writer(output_file, delimiter='\t',␣
 ↪quotechar='"', quoting=csv.QUOTE_NONE)
    header = ['set_id', 'set_of_integers']
    output_file_csv_writer.writerow(header)
    #
```

```
    input_file = open(input_file_name, 'r', encoding="utf-8")
    input_file_csv_reader = csv.reader(input_file,␣
↪delimiter=input_file_delimiter, quotechar=input_file_quotechar)
    next(input_file_csv_reader)
    for record in input_file_csv_reader:
        #
        doc_id = int(record[doc_id_column_idx])
        document = record[field_column_idx]
        #
        cleaned_document = cleaner(document, set__characters_of_interest)
        #
        set__shingle_id = shingler(cleaned_document, width=shingle_width)
        #
        output_file_csv_writer.writerow([doc_id, set__shingle_id])
        #
        #
        if doc_id % 1000 == 0:
            print("Last processed doc_id:", doc_id)
        #
    input_file.close()
    output_file.close()
    print("Last processed doc_id:", doc_id)
    print()
    print("max_shingle_id=", max_shingle_id)
    print()
    print()
    return max_shingle_id
```

[308]:
```
def is_prime(number):
    #
    if number == 2:
        return True
    if (number % 2) == 0:
        return False
    for j in range(3, int(number ** 0.5 + 1), 2):
        if (number % j) == 0:
            return False
    #
    return True
```

[309]:
```
def create_hash_functions(number_of_hash_functions,␣
↪upper_bound_on_number_of_distinct_elements, seed=42):
    random.seed(seed)
    #
    map__hash_function_id__a_b_p = {}
    #
    set_of_all_hash_functions = set()
```

```
    while len(set_of_all_hash_functions) < number_of_hash_functions:
        a = random.randint(1, upper_bound_on_number_of_distinct_elements - 1)
        b = random.randint(0, upper_bound_on_number_of_distinct_elements - 1)
        p = random.randint(upper_bound_on_number_of_distinct_elements, 10 *␣
↪upper_bound_on_number_of_distinct_elements)
        while is_prime(p) == False:
            p = random.randint(upper_bound_on_number_of_distinct_elements,
                               10 * upper_bound_on_number_of_distinct_elements)
        #
        c_hash_function = (a, b, p)
        set_of_all_hash_functions.add(c_hash_function)
    #
    for c_hash_function_id, c_hash_function in␣
↪enumerate(set_of_all_hash_functions):
        map__hash_function_id__a_b_p[c_hash_function_id] = c_hash_function
    #
    return map__hash_function_id__a_b_p
```

[310]:
```
def create_c_set_MinWiseHashing_sketch(c_set,
                                       map_as_list__index__a_b_p,
                                       total_number_of_hash_functions,␣
↪use_numpy_version = True):
    if use_numpy_version:
      app = np.array(map_as_list__index__a_b_p)
      c_set_MinWiseHashing_sketch = list(np.min((app[:,:1]*np.
↪array(list(c_set))[None,:]+app[:,1:2])%app[:,2:],axis=1))
    else:
      plus_inf = float("+inf")
      c_set_MinWiseHashing_sketch = [plus_inf] * total_number_of_hash_functions
      for c_element_id in c_set:
          for index, (a, b, p) in enumerate(map_as_list__index__a_b_p):
              c_hash_value = (a * c_element_id + b) % p
              if c_hash_value < c_set_MinWiseHashing_sketch[index]:
                  c_set_MinWiseHashing_sketch[index] = c_hash_value
              #
          #
      #
    return c_set_MinWiseHashing_sketch
```

[311]:
```
def create_MinWiseHashing_sketches(input_file_name,␣
↪upper_bound_on_number_of_distinct_elements,
                                   ␣
↪number_of_hash_functions_that_is_also_the_sketch_lenght_and_also_the_number_of_simulated_pe
                                   output_file_name, use_numpy_version=True):
    #
    map__hash_function_id__a_b_p = create_hash_functions(
```

```
    ␣
↪number_of_hash_functions_that_is_also_the_sketch_lenght_and_also_the_number_of_simulated_pe
        upper_bound_on_number_of_distinct_elements)
    #
    map__set_id__MinWiseHashing_sketch = {}
    #
    total_number_of_hash_functions = len(map__hash_function_id__a_b_p)
    # sorted_list_all_hash_function_id = sorted(map__hash_function_id__a_b_p.
↪keys())
    map_as_list__index__a_b_p = tuple([(a, b, p) for a, b, p in␣
↪map__hash_function_id__a_b_p.values()])
    #
    input_file = open(input_file_name, 'r', encoding="utf-8")
    input_file_csv_reader = csv.reader(input_file, delimiter='\t',␣
↪quotechar='"', quoting=csv.QUOTE_NONE)
    header = next(input_file_csv_reader)
    num_record_so_far = 0
    for record in input_file_csv_reader:
        num_record_so_far += 1
        if num_record_so_far % 100 == 0:
            print(num_record_so_far)
        c_set_id = int(record[0])
        c_set = eval(record[1])

        c_set_MinWiseHashing_sketch =␣
↪create_c_set_MinWiseHashing_sketch(c_set,map_as_list__index__a_b_p,
                                                                            ␣
↪total_number_of_hash_functions,
                                                                            ␣
↪use_numpy_version)

        #print(len(c_set_MinWiseHashing_sketch))
        map__set_id__MinWiseHashing_sketch[c_set_id] = c_set_MinWiseHashing_sketch
    input_file.close()
    #
    output_file = open(output_file_name, 'w', encoding="utf-8")
    output_file_csv_writer = csv.writer(output_file, delimiter='\t',␣
↪quotechar='"', quoting=csv.QUOTE_NONE)
    header = ['set_id', 'MinWiseHashing_sketch']
    output_file_csv_writer.writerow(header)
    sorted_list_all_set_id = sorted(map__set_id__MinWiseHashing_sketch.keys())
    for c_set_id in sorted_list_all_set_id:
        output_file_csv_writer.writerow([c_set_id,␣
↪str(map__set_id__MinWiseHashing_sketch[c_set_id])])
    output_file.close()
    #
```

```
    return
```

[312]:
```
def load_map__set_id__MinWiseHashing_sketch_from_file(input_file_name):
    map__set_id__MinWiseHashing_sketch = {}
    #
    input_file = open(input_file_name, 'r', encoding="utf-8")
    input_file_csv_reader = csv.reader(input_file, delimiter='\t',␣
↪quotechar='"', quoting=csv.QUOTE_NONE)
    header = next(input_file_csv_reader)
    for record in input_file_csv_reader:
        c_set_id = int(record[0])
        c_MinhiseHashing_sketch = tuple(eval(record[1]))
        #
        map__set_id__MinWiseHashing_sketch[c_set_id] = c_MinhiseHashing_sketch
        #
    input_file.close()
    #
    return map__set_id__MinWiseHashing_sketch
```

[313]:
```
def get_set_of_CANDIDATES_to_be_near_duplicates(r, b,␣
↪map__set_id__MinWiseHashing_sketch):
    #
    set_of_CANDIDATES_to_be_near_duplicates = set()
    #
    for c_band_progressive_id in range(b):
        #
        print("c_band_progressive_id", c_band_progressive_id)
        #
        c_band_starting_index = c_band_progressive_id * r
        c_band_ending_index = (c_band_progressive_id + 1) * r
        #
        map__band__set_set_id = {}
        #
        for c_set_id in map__set_id__MinWiseHashing_sketch:
            #
            if r * b != len(map__set_id__MinWiseHashing_sketch[c_set_id]):
                n = len(map__set_id__MinWiseHashing_sketch[c_set_id])
                message = "ERROR!!! n != r*b " + str(n) + "!=" + str(r * b) + ";
↪ " + str(n) + "!=" + str(r) + "*" + str(
                    b)
                raise ValueError(message)
            #
            c_band_for_c_set = tuple(
              ␣
↪map__set_id__MinWiseHashing_sketch[c_set_id][c_band_starting_index:
↪c_band_ending_index])
            #
```

```
            if c_band_for_c_set not in map__band__set_set_id:
                map__band__set_set_id[c_band_for_c_set] = set()
            map__band__set_set_id[c_band_for_c_set].add(c_set_id)
            #

        for c_set_set_id in map__band__set_set_id.values():
            #
            if len(c_set_set_id) > 1:
                #
                for set_id_a, set_id_A in it.combinations(c_set_set_id, 2):
                    if set_id_a < set_id_A:
                        set_of_CANDIDATES_to_be_near_duplicates.add((set_id_a,␣
↪set_id_A))
                    else:
                        set_of_CANDIDATES_to_be_near_duplicates.add((set_id_A,␣
↪set_id_a))
        #
    #
    return set_of_CANDIDATES_to_be_near_duplicates
```

[314]:

```
def compute_approximate_jaccard(set_a_MinWiseHashing_sketch,␣
↪set_b_MinWiseHashing_sketch):
    appx_jaccard = 0.
    #
    for index in range(len(set_a_MinWiseHashing_sketch)):
        #
        if set_a_MinWiseHashing_sketch[index] ==␣
↪set_b_MinWiseHashing_sketch[index]:
            appx_jaccard += 1
        #
    appx_jaccard /= len(set_a_MinWiseHashing_sketch)
    #
    return appx_jaccard
```

[315]:

```
def␣
↪compute_approximate_jaccard_to_REDUCE_the_number_of_CANDIDATES_to_be_near_duplicates(
        set_of_CANDIDATES_to_be_near_duplicates,
        map__set_id__MinWiseHashing_sketch, jaccard_threshold):
    map__set_a_id__set_A_id__appx_jaccard = {}
    #
    for set_a_id, set_A_id in set_of_CANDIDATES_to_be_near_duplicates:
        #
        set_a_MinWiseHashing_sketch =␣
↪map__set_id__MinWiseHashing_sketch[set_a_id]
        set_A_MinWiseHashing_sketch =␣
↪map__set_id__MinWiseHashing_sketch[set_A_id]
```

```
        #
        appx_jaccard = compute_approximate_jaccard(set_a_MinWiseHashing_sketch,␣
↪set_A_MinWiseHashing_sketch)
        #
        if appx_jaccard >= jaccard_threshold:
            map__set_a_id__set_A_id__appx_jaccard[(set_a_id, set_A_id)] =␣
↪appx_jaccard
        #
    #
    return map__set_a_id__set_A_id__appx_jaccard
```

[316]:

```
def mine_couples_of_Near_Duplicates(input_file_name, r, b, jaccard_threshold):
    #
    print("Starting the loading of the MinWiseHashing sketches from the input␣
↪file.")
    map__set_id__MinWiseHashing_sketch =␣
↪load_map__set_id__MinWiseHashing_sketch_from_file(input_file_name)
    print()
    print("Number of sets=", len(map__set_id__MinWiseHashing_sketch))
    print()
    #
    print("Starting the mining of the CANDIDATES couples to be near duplicates.
↪")
    set_of_CANDIDATES_to_be_near_duplicates =␣
↪get_set_of_CANDIDATES_to_be_near_duplicates(r, b,
                                                                                    ␣
↪          map__set_id__MinWiseHashing_sketch)
    #
    print()
    print("Number of pairs of sets to be near-duplicate CANDIDATES=",␣
↪len(set_of_CANDIDATES_to_be_near_duplicates))
    print()
    #
    map__set_a_id__set_A_id__appx_jaccard =␣
↪compute_approximate_jaccard_to_REDUCE_the_number_of_CANDIDATES_to_be_near_duplicates(
        set_of_CANDIDATES_to_be_near_duplicates,␣
↪map__set_id__MinWiseHashing_sketch, jaccard_threshold)
    print()
    print("Number of REFINED pairs of sets to be near-duplicate CANDIDATES=",
          len(map__set_a_id__set_A_id__appx_jaccard))
    print()
    #
    output_file = open(output_file_name, 'w', encoding="utf-8")
    output_file_csv_writer = csv.writer(output_file, delimiter='\t',␣
↪quotechar='"', quoting=csv.QUOTE_NONE)
    header = ['set_a_id', 'set_b_id', 'approximate_jaccard']
```

```
    output_file_csv_writer.writerow(header)
    sorted_list_all_set_id = sorted(map__set_id__MinWiseHashing_sketch.keys())
    for set_a_id__set_A_id in map__set_a_id__set_A_id__appx_jaccard:
        appx_jaccard = map__set_a_id__set_A_id__appx_jaccard[set_a_id__set_A_id]
        output_file_csv_writer.writerow([set_a_id__set_A_id[0],␣
↪set_a_id__set_A_id[1], appx_jaccard])
    output_file.close()
    return
```

2.1 Part 2.1

2.1.1 2.1.1

Download the dataset from the Drive link (code already provided).

[ ]:
```
#REMOVE_OUTPUT#
!gdown 16LQDmla82XFK1B0lr8H9ycm01pxjURXN
```

2.1.2 2.1.2

Inspect the dataset: print the list of fields names. Print the value of the `song` field for the last 3 documents.

[318]:
```
#YOUR CODE STARTS HERE#
df_songs = pd.read_csv('150K_lyrics_from_MetroLyrics.csv')
print("The list of flieds names in the dataset: \n", list(df_songs.columns))
print("\n")
print("The value of the song field for the last 3 documents:")
df_songs.tail(3)

#YOUR CODE ENDS HERE#
#THIS IS LINE 20#
```

```
The list of flieds names in the dataset:
 ['ID', 'song', 'year', 'artist', 'genre', 'lyrics']
```

```
The value of the song field for the last 3 documents:
```

[318]:

```
            ID                       song  year        artist genre  \
149997  209048  oh-what-a-fool-i-have-been  2007  gary-glitter  rock
149998  209049                  lonely-boy  2007  gary-glitter  rock
149999  209050             sidewalk-sinner  2007  gary-glitter  rock

                                                   lyrics
149997  oh what a fool i've been you changed this begg…
149998  i'm just a lonely boy lonely and blue i'm all …
149999  a long the grooviest street in town you're tre…
```

2.1.3 2.1.3

Turn the lyrics field of each document into a sets of shingles of length 4 and save the result to a file named `hw1_set_id_set_of_integers.tsv`

[ ]:

```
#REMOVE_OUTPUT#
#YOUR CODE STARTS HERE#
set__characters_of_interest = set(
    [' ', '0', '1', '2', '3', '4', '5', '6', '7', '8', '9', 'a', 'b', 'c', 'd',␣
↪'e', 'f', 'g', 'h', 'i', 'j', 'k', 'l',
     'm', 'n', 'o', 'p', 'q', 'r', 's', 't', 'u', 'v', 'w', 'x', 'y', 'z'])
max_shingle_id = -1
map__shingle__shingle_id = {}
input_file_name = "150K_lyrics_from_MetroLyrics.csv"
input_file_delimiter = ','
input_file_quotechar = '"'
output_file_name = "hw1_set_id_set_of_integers.tsv"
shingle_width = 4
doc_id_column_idx = 0
field_column_idx = 5
max_shingle_id = create_sets_of_shingle_ids(input_file_name, output_file_name,␣
↪input_file_delimiter,
                                            input_file_quotechar,␣
↪set__characters_of_interest, shingle_width,
                                            doc_id_column_idx, field_column_idx)

#YOUR CODE ENDS HERE#
#THIS IS LINE 20#
```

2.1.4 2.1.4

Load the file containing the sets of shingles and apply MinWiseHashing, saving the result into a file named `hw1_set_id_MinWiseHashing_sketch.tsv`. Choose the number of hash functions (n) in relation to the constraints highlighted at the beginning of part 2. Provide an explanation for your choice in **exactly one sentence**.

————YOUR TEXT STARTS HERE————

We choose **200** as the number of hash functions n because it seem to us to be a **good compromise** between a fast system (too many hash functions would have slowed down the next phase of LSH) and one that can lead to accurate results.

[ ]:
```
#REMOVE_OUTPUT#
#YOUR CODE STARTS HERE#
input_file_name = "hw1_set_id_set_of_integers.tsv"
output_file_name = "hw1_set_id_MinWiseHashing_sketch.tsv"

number_of_hash_functions_that_is_also_the_sketch_length_and_also_the_number_of_simulated_permu
 ↪= 200

create_MinWiseHashing_sketches(input_file_name, max_shingle_id,
                                ␣
 ↪number_of_hash_functions_that_is_also_the_sketch_length_and_also_the_number_of_simulated_pe
                                output_file_name)









#YOUR CODE ENDS HERE#
#THIS IS LINE 20#
```

2.1.5 2.1.5

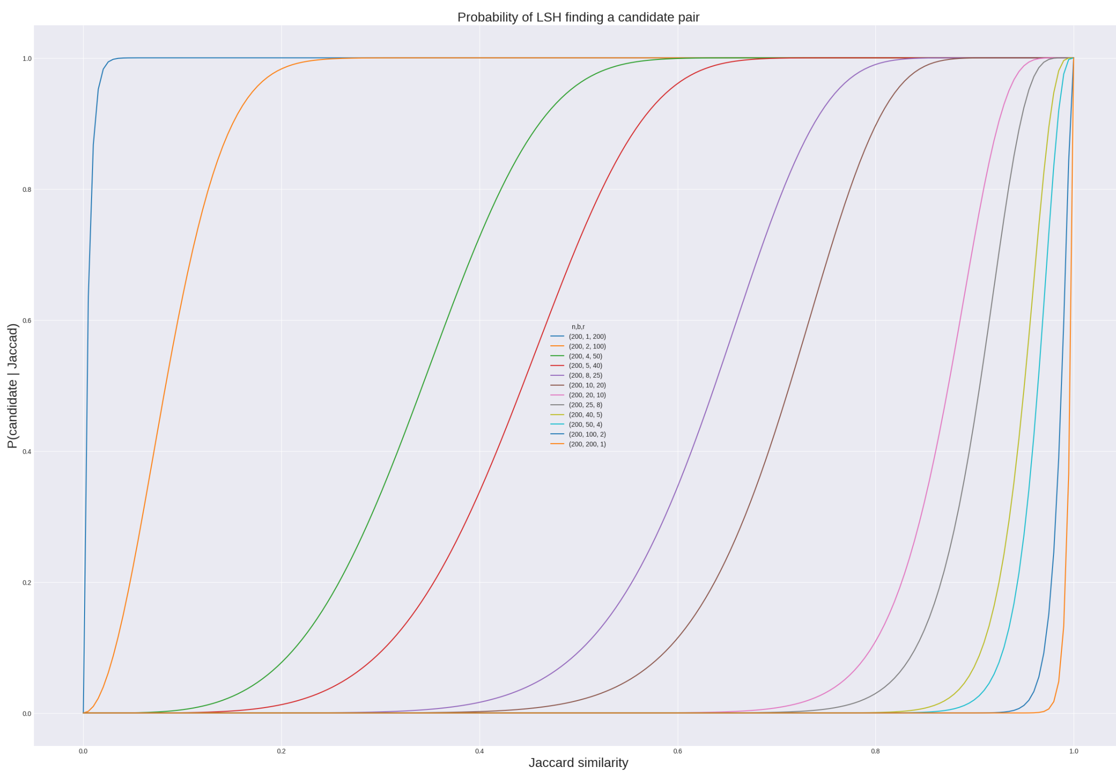
To perform Locality Sensivity Hashing, you have to choose the number of rows (r) and the number bands (b). List all the possible choices of r and b that satisfy the constraints highlighted at the beginning of part 2, according to the number of hash functions you chose.

For all of these configurations, plot all the associated S-curves. The S-curve is defined as the probability (y-axis) that a pair of documents with Jaccard similarity j (x-axis) is selected as a near-duplicate candidate given r and b. Plot all S-curves in the same plot.

[321]:
```
#YOUR CODE STARTS HERE#
df = pd.DataFrame(data =[(1, 200), (2, 100), (4, 50), (5, 40), (8, 25), (10,␣
 ↪20), (20, 10), (25,8), (40, 5), (50, 4), (100, 2), (200, 1)], columns=['b',␣
 ↪'r'])
df['n'] = df['b'] * df['r']
for j in np.linspace(0, 1, 200):
    df[j] = 1 - (1 - j**df['b']) ** df['r']

df = pd.pivot_table(df, index=['n', 'b', 'r'])

ax = df.T.plot(figsize=(30, 20))
plt.ylabel('P(candidate | Jaccad)', fontsize = 20)
plt.xlabel('Jaccard similarity', fontsize = 20)
plt.title('Probability of LSH finding a candidate pair', fontsize = 20)
```

```
#YOUR CODE ENDS HERE#
#THIS IS LINE 30#
```

[321]: Text(0.5, 1.0, 'Probability of LSH finding a candidate pair')



2.1.6 2.1.6

Among all the configurations you plotted in the previous step, choose the one that gives the smallest amount of False-Positives and False-Negatives near-duplicates candidates, satisfying the provided constraints. You **must** take into account, that after the LSH procedure, the approximate Jaccard similarity between near-duplicate candidates is computed and used to reduce their number.

Provide an explanation for your choice in **at most 3 sentences**.

[322]:
```
#YOUR CODE STARTS HERE#
r = 20
b = 10
#YOUR CODE ENDS HERE#
#THIS IS LINE 5#
```

————YOUR TEXT STARTS HERE————

The *rightmost S-curves* in the plot are those with **high b** so also a higher number of False-Positives candidates (lower similarity threshold), while the *leftmost S-curves* are those with **lower b** so also a higher number of False-Negatives candidates (higher similarity threshold).

A number of bands *b equal to 10* and a number of rows *r equal to 20* (the brown S-curve in the plot) turned out to be the solution that fit better our dataset because, being in an **intermediate configuration**, we generate the smallest amount of both False-Negatives and False-Positives (which will then be removed with the approximate Jaccard Similarity) .

2.1.7 2.1.7

Load the file containing the MinWiseHashing sketches and perform Locality Sensivity Hashing, using the parameters you chose in last step, considering also the computation of approximate Jaccard to reduce the number of candidates. Save the Near-Duplicates candidates obtained to a file named `hw1_NearDuplicates_set_a_id_set_b_id_approximate_jaccard.tsv`.

Print the execution time.

[323]:
```python
#YOUR CODE STARTS HERE#
jaccard_threshold = 0.93
input_file_name = "hw1_set_id_MinWiseHashing_sketch.tsv"
output_file_name = "hw1_NearDuplicates_set_a_id_set_b_id_approximate_jaccard.
↪tsv"
start_time = time.time()
mine_couples_of_Near_Duplicates(input_file_name, r, b, jaccard_threshold)
end_time = time.time()
print("The execution time is:", end_time-start_time, "seconds.")






















#YOUR CODE ENDS HERE#
#THIS IS LINE 30#
```

```
Starting the loading of the MinWiseHashing sketches from the input file.

Number of sets= 150000

Starting the mining of the CANDIDATES couples to be near duplicates.
c_band_progressive_id 0
c_band_progressive_id 1
c_band_progressive_id 2
```

```
c_band_progressive_id 3
c_band_progressive_id 4
c_band_progressive_id 5
c_band_progressive_id 6
c_band_progressive_id 7
c_band_progressive_id 8
c_band_progressive_id 9

Number of pairs of sets to be near-duplicate CANDIDATES= 18831


Number of REFINED pairs of sets to be near-duplicate CANDIDATES= 17177

The execution time is: 65.42058444023132 seconds.
```

2.1.8 2.1.8

Load the file containing the number of near-duplicates candidates. Print the number of near-duplicates candidates you found.

[324]:
```
#YOUR CODE STARTS HERE#
output_file = pd.
 ↪read_csv("hw1_NearDuplicates_set_a_id_set_b_id_approximate_jaccard.tsv",␣
 ↪delimiter = "\t")
print("At the end of the LSH, we found", output_file.shape[0], "near-duplicates␣
 ↪candidates.\n")
print("First 10 candidate pairs in the file:\n\n", output_file.loc[:10])
```

```
#YOUR CODE ENDS HERE#
#THIS IS LINE 30#
```

```
At the end of the LSH, we found 17177 near-duplicates candidates.

First 10 candidate pairs in the file:

     set_a_id  set_b_id  approximate_jaccard
0       84406    142635                  1.0
1       93123     93130                  1.0
2       66462     98489                  1.0
3      118894    118976                  1.0
4       55585    129461                  1.0
5      183011    183054                  1.0
6      118924    119084                  1.0
7      118957    119032                  1.0
8      118943    119097                  1.0
9      127105    127205                  1.0
10       4543    129016                  1.0
```

2.2 Part 2.2

You will be given a scenario and you will have to provide the best solution.

2.2.1 2.2.1

Let us consider the same scenario as in Part 2.1, with the only addition of not wanting more than 100 False Negatives. How would the choice of the LSH configuration change? Would you need any more information to satisfy the new constraint?

————YOUR TEXT STARTS HERE————

We may compute the number of False-Negatives as the *probability that two documents D1 and D2 are not similar in all b bands* and it is reasonable to assume that **this probability is very low if b is high enough**.

`P(D1 and D2 are not similar in all b bands) = (1 - (Jaccard)^r)^b`

The LSH configurations that respect the constraint that False-Negatives candidates are less than 100 are those where **b is greater than or equal to 20** (the rightmost S-curves) because increasing the bands also increases the probability of finding the most similar candidate pairs.

In this way, the number of False-Positives and that of False-Negatives is no longer balanced: we would also need a maximum number of False-Positives to choose a reasonable and not too high b.