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# A SIMPLE SEARCH SYSTEM FOR PHRASE AND PROXIMITY QUERIES

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## ABSTRACT

In this assignment, we are expected to implement a document retrieval system for phrase and proximity queries using the *positional inverted indexing scheme*. We will use the Reuters-21578 data set for this purpose. Reuters-21578 contains 21578 news stories from Reuters newswire. There are 22 SGML files, each containing 1000 news articles, except the last file, which contains 578 articles. We are expected to preprocess the data set, build the inverted index and implement a query processor.

## 1 Data Preprocessing

Firstly, we start our data preprocessing procedure by parsing the news from the Reuters dataset. We extract **<TITLE>** and **<BODY>** tags of each news. *NEWID* fields are used as document IDs. A set of regex patterns are used to extract relevant information. Documents are stored in a dictionary where *key* corresponds to document IDs and *value* corresponds to smaller dictionaries composed of a title and body for each text. After collecting all the textual information, we feed these documents into the tokenization pipeline. Our pipeline roughly consists of five steps: HTML unescaping, punctuation removal, splitting, case-folding and stemming.

In HTML, escaping involves substituting certain special characters with alternative ones, typically `<`, `>`, `"`, `$`, and `&`. These characters hold distinct purposes within HTML documents. The fundamental idea of escaping is to encrypt the characters `<` and `>` and apostrophes to make them less identifiable as tags. Escaping HTML has a variety of uses, the most obvious of which is that it can be inserted into an HTML document without rendering to show code. It can be observed that our dataset contains examples of HTML escaping. We have to eliminate escaping characters before proceeding with tokenization. For this purpose, the built-in [html](#) (HyperText Markup Language support) library can be used in Python.

After removing the escape characters, we can remove the punctuation and digits. To remove the punctuation, we simply used the list in [string.punctuation](#) provided within the standard library. Upon removal of punctuation and digits, we split the text into tokens by whitespaces. This operation changes our data structure from *string* to *list*. Now we have a list of tokens in our hands.

Now, we apply *case-folding* to each token in our list, by reducing all letters to lowercase. Case-folding helps us to match instances of different words at the beginning of a sentence with the query of those words. On the other hand, such case folding can equate words that might better be kept apart (such as *Fed* and *fed*) [1, p. 30]. Case-folding doesn't reduce the number of tokens we have - but it is very likely to reduce the number of *unique* tokens in the corpus.

Lastly, we apply *stemming* to each token in the list. We used a slightly modified version of the Porter Stemming algorithm, which has proved to be one of the most effective stemming algorithms empirically, provided here [2]. The goal of both stemming is to reduce inflectional forms and sometimes derivationally related forms of a word to a common base form [1, p. 32]. After the stemming procedure, the number of unique tokens decreases since some of the different tokens will be reduced to the same root.

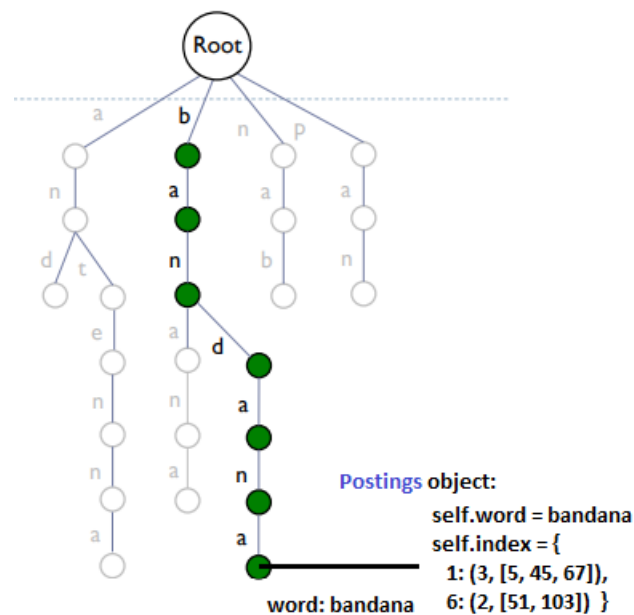
- *How many tokens does the corpus contain before and after case-folding?*: We don't expect the number of tokens to change upon case-folding. We had 2,644,987 tokens both before and after case-folding.
- *How many terms (unique tokens) are there before and after case-folding?*: We expected the number of tokens to change upon case-folding. Before the case folding we had 58,617 unique tokens, whereas after the case folding we had 42,574 unique tokens in the corpus. After case-folding, we apply stemming on the words. As a result of the stemming operation, we get 31,760 unique tokens in our corpus.
- *List the top 100 most frequent terms after case-folding*: Below, you can find the top 100 most frequent words both after case-folding (before stemming) and after stemming side by side. As you can see, most frequent words are usually stopwords in English:

1	After case-folding (before stemming)	After stemming
2	the: 144423	the: 144423
3	of: 73605	of: 73615
4	to: 73073	to: 73074
5	in: 54939	in: 54942
6	and: 54545	and: 54549
7	said: 53096	said: 53096
8	a: 52169	a: 52169
9	s: 32871	it: 37881
10	for: 27306	s: 32871
11	mln: 26732	for: 27306
12	it: 22882	mln: 26745
13	dlrs: 21273	on: 25309
14	on: 19392	dlr: 24681
15	reuter: 18966	reuter: 20036
16	pct: 18046	pct: 18046
17	is: 16875	is: 16875
18	that: 15527	be: 15923
19	from: 15277	that: 15527
20	by: 15154	year: 15386
21	its: 14995	from: 15277
22	will: 14855	by: 15154
23	vs: 14836	will: 15042
24	be: 14738	vs: 14836
25	at: 14517	at: 14525
26	with: 13706	with: 13706
27	year: 13109	bank: 12332
28	was: 11938	wa: 11938
29	u: 11326	compani: 11520
30	billion: 10726	u: 11326
31	he: 10676	billion: 10756
32	has: 10185	he: 10676
33	company: 9699	ha: 10224
34	as: 9694	share: 10220
35	an: 9590	as: 9695
36	cts: 9219	an: 9594
37	would: 9200	ct: 9457
38	not: 8308	would: 9201
39	inc: 8161	market: 8485
40	bank: 8018	not: 8309
41	net: 7698	inc: 8161
42	which: 7556	new: 8159
43	new: 7182	net: 7712
44	corp: 7171	which: 7556
45	but: 7141	trade: 7498
46	are: 7043	price: 7469
47	this: 6855	corp: 7192
48	have: 6758	but: 7142
49	were: 6262	ar: 7052
50	market: 5959	have: 6989
51	last: 5915	thi: 6856
52	one: 5873	stock: 6713
53	stock: 5705	loss: 6398

54	had: 5685		were: 6262
55	loss: 5626		rate: 5961
56	or: 5510		last: 5955
57	shares: 5238		or: 5720
58	also: 5174		had: 5692
59	up: 5160		sale: 5680
60	about: 5118		offer: 5431
61	they: 5098		shr: 5391
62	two: 5073		up: 5249
63	share: 4865		also: 5174
64	trade: 4746		about: 5118
65	co: 4736		thei: 5099
66	been: 4501		two: 5073
67	shr: 4293		unit: 4914
68	oil: 4272		oper: 4894
69	may: 4258		co: 4840
70	debt: 4094		product: 4704
71	sales: 4070		oil: 4506
72	government: 4034		expect: 4505
73	first: 4014		been: 4501
74	more: 3958		profit: 4405
75	april: 3804		month: 4369
76	after: 3738		issu: 4344
77	march: 3640		govern: 4326
78	exchange: 3607		debt: 4290
79	group: 3459		mai: 4274
80	over: 3457		industri: 4249
81	than: 3442		report: 4216
82	dlr: 3408		plan: 4126
83	japan: 3381		offici: 4096
84	other: 3356		first: 4014
85	profit: 3329		increas: 4010
86	prices: 3315		exchang: 3988
87	three: 3253		more: 3958
88	we: 3249		end: 3877
89	price: 3249		note: 3821
90	banks: 3242		april: 3804
91	per: 3151		after: 3738
92	no: 3134		group: 3734
93	rate: 3099		export: 3718
94	international: 3094		week: 3675
95	their: 3088		march: 3650
96	ltd: 3064		other: 3633
97	week: 3014		interest: 3544
98	interest: 3004		secur: 3504
99	foreign: 2987		over: 3457
100	some: 2945		than: 3442
101	told: 2913		includ: 3417

## 2 Inverted Index

**Positional** inverted indexing scheme is used to store the words, document frequency, and positions. In the positional inverted index, for each term in the vocabulary, we store postings of the form `<docID: position1, position2, ...>` where each position is a token index in the document. Each posting will also usually record the term frequency. For the final version of the vocabulary, I've used [Trie](#) data structure. My *Trie* implementation consists of *TrieNode* objects, where each node corresponds to a character. For the posting lists, I implemented another data structure called *Posting*, which stores the word, document frequency and a **dictionary** of postings in the form given above. Only the nodes corresponding to the end of the words (last character), are associated with a *Posting* object. To exemplify, let's say the word "bandana" occurs in two documents with IDs 1 and 6. In the first document, it occurs at positions 5, 45, and 67. In the second document, it occurs at positions 51 and 103. In this scenario, we can visualize trie and inverted index scheme as follows:



We can easily calculate the term frequency by adding the lengths of the position lists and document frequency by getting the number of keys in the dictionary, if necessary.

## 3 Screenshots

- Provide a screenshot of running the indexing module of your system

```
PROBLEMS  OUTPUT  DEBUG CONSOLE  TERMINAL

PS C:\Users\karab\Desktop\cmpe493\assignment1> python dataprocessor.py
> Reading the news dataset. Creating a dictionary of documents with TITLE and BODY components.
Number of news texts without titles: 737
Number of news texts without body: 2535
> News are read and a dictionary of documents is created. Elapsed time: 0.697 seconds
> Proceeding with tokenization for news texts. Positional indexes will be prepared.
Processing: HTML Unescape --> Remove Punctuation --> Remove Digits --> Split --> Case Folding --> Stemming
Number of (total) tokens before casefolding: 2644987
Number of (total) tokens after casefolding: 2644987
Number of unique tokens before casefolding: 58617
Number of unique tokens after casefolding: 42574
Number of unique tokens after stemming: 31760
> Tokenization is completed. Positional indexes are generated. Elapsed time: 24.054 seconds
> Positional indexes are being dumped with Pickle.
> Positional indexes are dumped at vocab.pickle. Elapsed time: 3.815 seconds
PS C:\Users\karab\Desktop\cmpe493\assignment1>
```

- Provide two screenshots of running your system for each of the two types of queries.

- (i) Proximity query: coffee 2 market  
Phrase query: "coffee market"

```

PROBLEMS OUTPUT DEBUG CONSOLE TERMINAL
PS C:\Users\karab\Desktop\cmpe493\assignment1> python queryprocessor.py long 3 impact
> Reading the positional indexes and creating a query processor.
> Query processor is created. Elapsed time: 8.521 seconds
List of documents: [3987, 4001, 7502, 19870]
PS C:\Users\karab\Desktop\cmpe493\assignment1> python queryprocessor.py "long term impact"
> Reading the positional indexes and creating a query processor.
> Query processor is created. Elapsed time: 4.21 seconds
List of documents: [3987, 4001]
PS C:\Users\karab\Desktop\cmpe493\assignment1>

```

- (ii) Proximity query: long 3 impact  
Phrase query: "long term impact"

```

PROBLEMS OUTPUT DEBUG CONSOLE TERMINAL powershell - assignment1
(env) PS C:\Users\karab\Desktop\cmpe493\assignment1> python queryprocessor.py coffee 2 market
> Reading the positional indexes and creating a query processor.
> Query processor is created. Elapsed time: 3.3 seconds
List of documents: [232, 754, 1312, 1579, 1880, 1889, 2467, 2606, 2954, 3034, 3559, 4147, 4267, 4603, 4785, 5134, 5471, 6912, 7888, 8193, 8200, 9654, 10752, 11866, 12465, 12655, 12701, 14372, 14606, 16097, 19387, 21567]
(env) PS C:\Users\karab\Desktop\cmpe493\assignment1> python queryprocessor.py "coffee market"
> Reading the positional indexes and creating a query processor.
> Query processor is created. Elapsed time: 3.2 seconds
List of documents: [232, 754, 1579, 1880, 1889, 2467, 2606, 3034, 3559, 4147, 4603, 4785, 5134, 5471, 6912, 7888, 8193, 8200, 9654, 10752, 12465, 12655, 12701, 14372, 14606, 16097, 19387, 21567]
(env) PS C:\Users\karab\Desktop\cmpe493\assignment1>

```

## References

- [1] Christopher D. Manning, Prabhakar Raghavan, and Hinrich Schütze. *An Introduction to Information Retrieval*. Cambridge University Press, 2008.
- [2] Martin Porter. Python implementation of the porter stemming algorithm, 2002.