山东大学　　计算机科学与技术　　学院

信息检索与数据挖掘 课程实验报告

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实验题目：预处理文本数据集，并且得到每个文本的 VSM 表示。

实验内容：

#Homework 1: VSM
#预处理文本数据集，并且得到每个文本的 VSM 表示。
The 20 Newsgroups dataset is a collection of approximately 20,000 newsgroup documents, partitioned (nearly) evenly across 20 different newsgroups.
#20news-18828.tar.gz (http://qwone.com/~jason/20Newsgroups/20news-18828.tar.gz) ?- 20 Newsgroups; duplicates removed, only "From" and "Subject" headers (18828 documents)

实验环境：

Spyder+python3.6
Win10

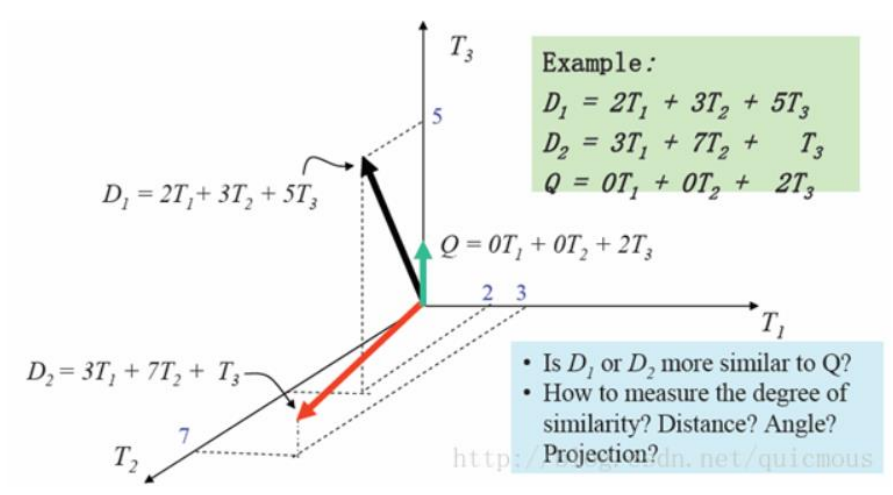
实验过程中遇到和解决的问题：

（记录实验过程中遇到的问题，以及解决过程和实验结果。可以适当配以关键代码辅助说明，但不要大段贴代码。）

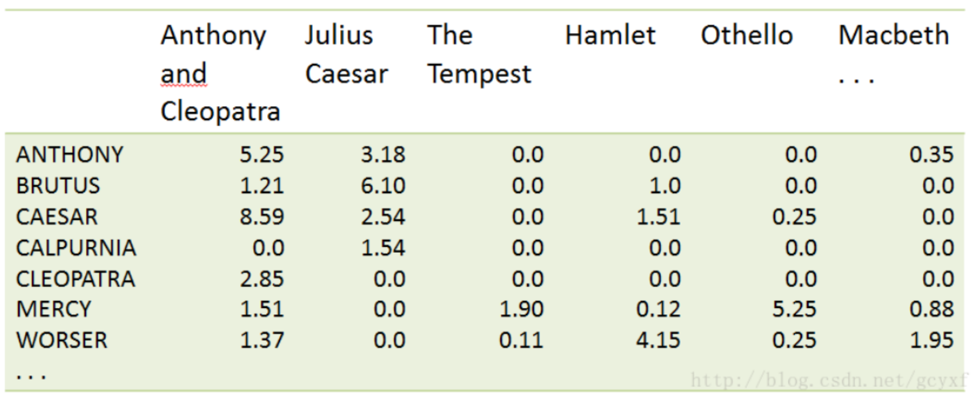
一、实现前相关准备

查阅相关 VSM 的资料，在此感谢以下网页所提供的内容：
http://allmybrain.com/2007/10/19/similarity-of-texts-the-vector-space-model-with-python/
http://blog.josephwilk.net/projects/building-a-vector-space-search-engine-in-python.html/
https://blog.csdn.net/quicmous/article/details/71263844/

向量空间模型中将文本表达为一个向量，看作向量空间中的一个点。


T_3
Example:
$D_1 = 2T_1 + 3T_2 + 5T_3$
$D_2 = 3T_1 + 7T_2 + T_3$
$Q = 0T_1 + 0T_2 + 2T_3$
5
$D_1 = 2T_1 + 3T_2 + 5T_3$
$Q = 0T_1 + 0T_2 + 2T_3$
2 3
T_1
$D_2 = 3T_1 + 7T_2 + T_3$
7
T_2
• Is D_1 or D_2 more similar to Q?
• How to measure the degree of similarity? Distance? Angle? Projection?
http://blog.csdn.net/quicmous

下面，就到了最关键的部分。基于tf-idf，我们将得到Weight Matrix （权重矩阵）。



	Anthony and Cleopatra	Julius Caesar	The Tempest	Hamlet	Othello	Macbeth ...
ANTHONY	5.25	3.18	0.0	0.0	0.0	0.35
BRUTUS	1.21	6.10	0.0	1.0	0.0	0.0
CAESAR	8.59	2.54	0.0	1.51	0.25	0.0
CALPURNIA	0.0	1.54	0.0	0.0	0.0	0.0
CLEOPATRA	2.85	0.0	0.0	0.0	0.0	0.0
MERCY	1.51	0.0	1.90	0.12	5.25	0.88
WORSER	1.37	0.0	0.11	4.15	0.25	1.95
...						

二、Python 代码实现过程中所遇问题

1. 所有文档读取的实现，探索后使用 os 模块内的函数能高效完成，如下所示：

```
# 测试文档路径
Newspath=(r"C:\Users\93568\Documents\GitHub\DataMining\Homework1VSM\20news-18828")
#小规模测试文档路径
#Newspath=(r"C:\Users\93568\Documents\GitHub\0123")
folders=[f for f in  os.listdir(Newspath)]
print(folders)
files=[]
for folderName in  folders:
    folderPath=os.path.join(Newspath, folderName)
    files.append([f for f in os.listdir(folderPath)])

document_filenames={}
i=0
for fo in range(len(folders)):
    for fi in files[fo] :
        document_filenames.update({i:os.path.join(Newspath,os.path.join(folders[fo],fi))})
        i+=1
```

2. Gbk 和 uincode 编码传换问题：

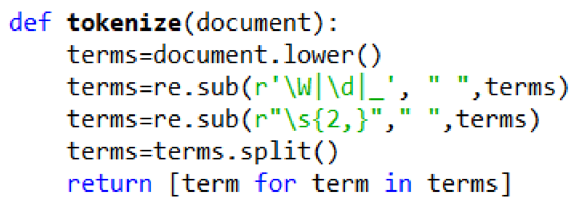
```
document = f.read()
```

```
UnicodeDecodeError: 'gbk' codec can't decode byte 0xff in position
11597: illegal multibyte sequence
```

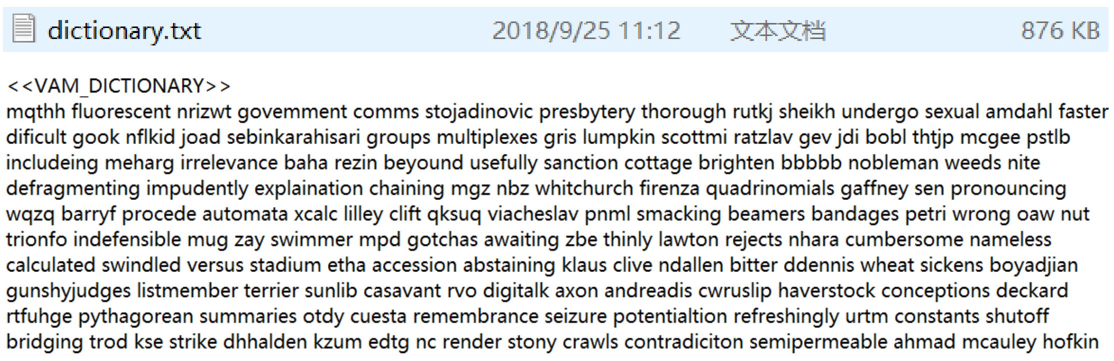
改变编码方式，忽略错误后，修改代码如下完美解决：

```
f = open(Newspath,'r',encoding='utf-8',errors='ignore')
fp=open(r"**** \GitHub\dictionary.txt",'w',encoding='utf-8')
```

3. 文档预处理 takenize 相关问题：
   使用 lower()、split()以及 strip(characters)后发现效果不理想，创建得词典太大而且杂乱，打印到 txt 文档后居然有 3M 多，于是决定使用正则化的 re.sub()，去掉除字母外的所有符号字符（包括数字），得到纯单词，测试后得到的词典效果大为好转，如下：



```python
def tokenize(document):
    terms=document.lower()
    terms=re.sub(r'\W|\d|_', " ",terms)
    terms=re.sub(r"\s{2,}"," ",terms)
    terms=terms.split()
    return [term for term in terms]
```



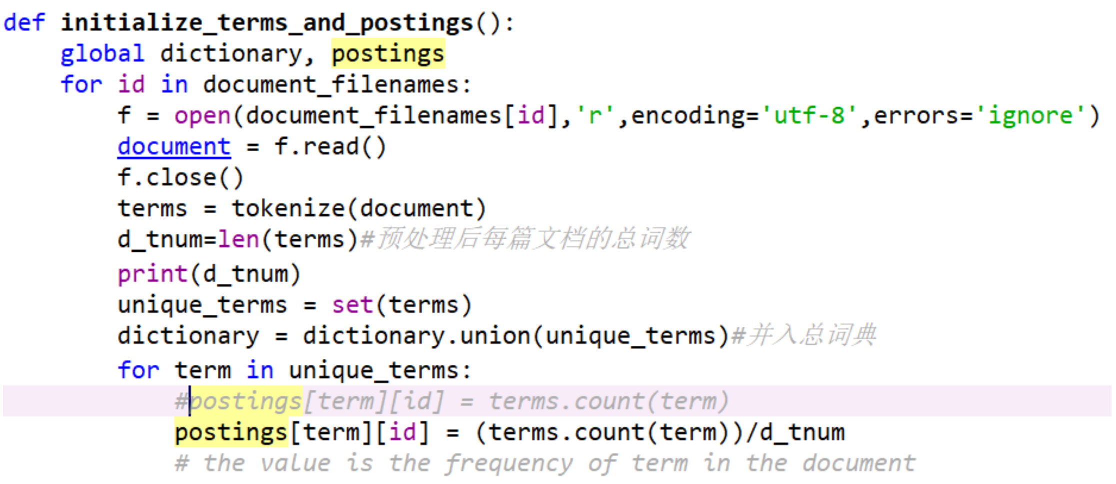
```
dictionary.txt                    2018/9/25 11:12     文本文档          876 KB
```

```
<<VAM_DICTIONARY>>
mqthh fluorescent nrizwt govemment comms stojadinovic presbytery thorough rutkj sheikh undergo sexual amdahl faster
dificult gook nflkid joad sebinkarahisari groups multiplexes gris lumpkin scottmi ratzlav gev jdi bobl thtjp mcgee pstlb
includeing meharg irrelevance baha rezin beyound usefully sanction cottage brighten bbbbb nobleman weeds nite
defragmenting impudently explaination chaining mgz nbz whitchurch firenza quadrinomials gaffney sen pronouncing
wqzq barryf procede automata xcalc lilley clift qksuq viacheslav pnml smacking beamers bandages petri wrong oaw nut
trionfo indefensible mug zay swimmer mpd gotchas awaiting zbe thinly lawton rejects nhara cumbersome nameless
calculated swindled versus stadium etha accession abstaining klaus clive ndallen bitter ddennis wheat sickens boyadjian
gunshyjudges listmember terrier sunlib casavant rvo digitalk axon andreadis cwruslip haverstock conceptions deckard
rtfuhge pythagorean summaries otdy cuesta remembrance seizure potentialtion refreshingly urtm constants shutoff
bridging trod kse strike dhhalden kzum edtg nc render stony crawls contradiciton semipermeable ahmad mcauley hofkin
```

4. 向量权重取值计算，TF/IDF 相关方法代码实现：

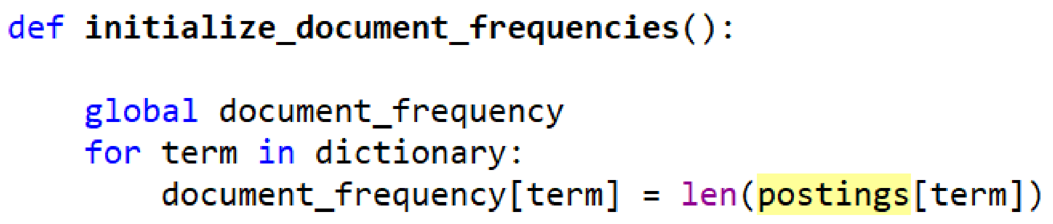
$$TF - IDF = tf * idf$$

计算词频(tf)：

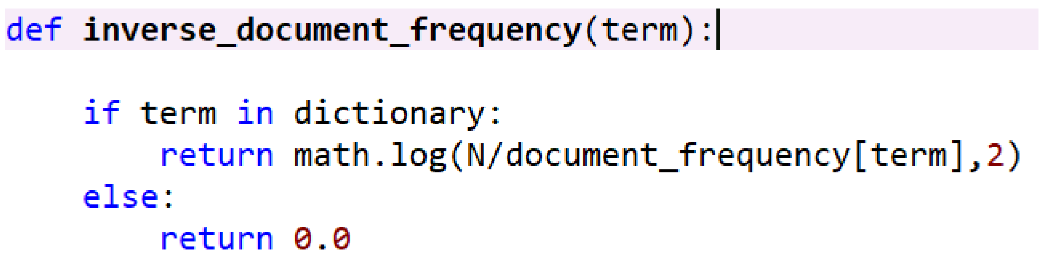


```python
def initialize_terms_and_postings():
    global dictionary, postings
    for id in document_filenames:
        f = open(document_filenames[id],'r',encoding='utf-8',errors='ignore')
        document = f.read()
        f.close()
        terms = tokenize(document)
        d_tnum=len(terms)#预处理后每篇文档的总词数
        print(d_tnum)
        unique_terms = set(terms)
        dictionary = dictionary.union(unique_terms)#并入总词典
        for term in unique_terms:
            #postings[term][id] = terms.count(term)
            postings[term][id] = (terms.count(term))/d_tnum
            # the value is the frequency of term in the document
```

计算 df 及 idf:

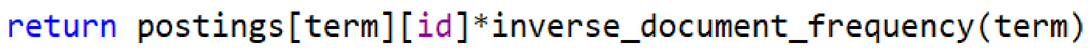


```python
def initialize_document_frequencies():

    global document_frequency
    for term in dictionary:
        document_frequency[term] = len(postings[term])
```



```
def inverse_document_frequency(term):

    if term in dictionary:
        return math.log(N/document_frequency[term],2)
    else:
        return 0.0
```

计算权重：

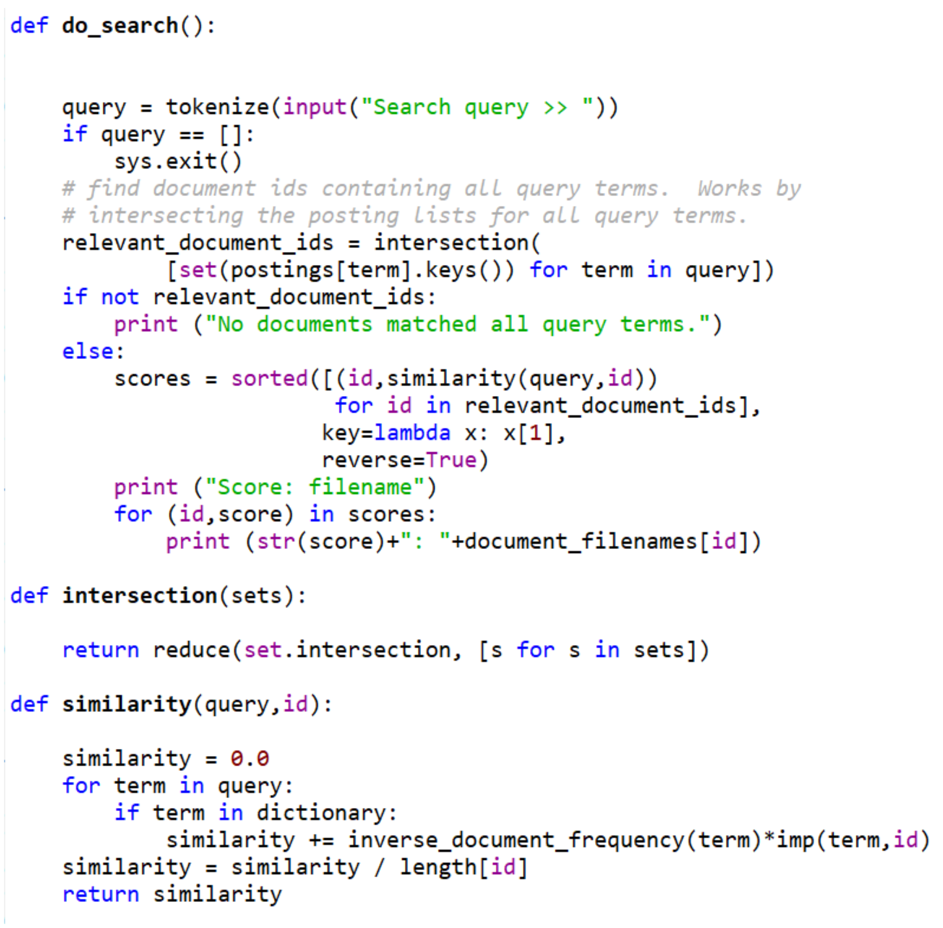


```
return postings[term][id]*inverse_document_frequency(term)
```

三、 在已有实现上新增功能应用：

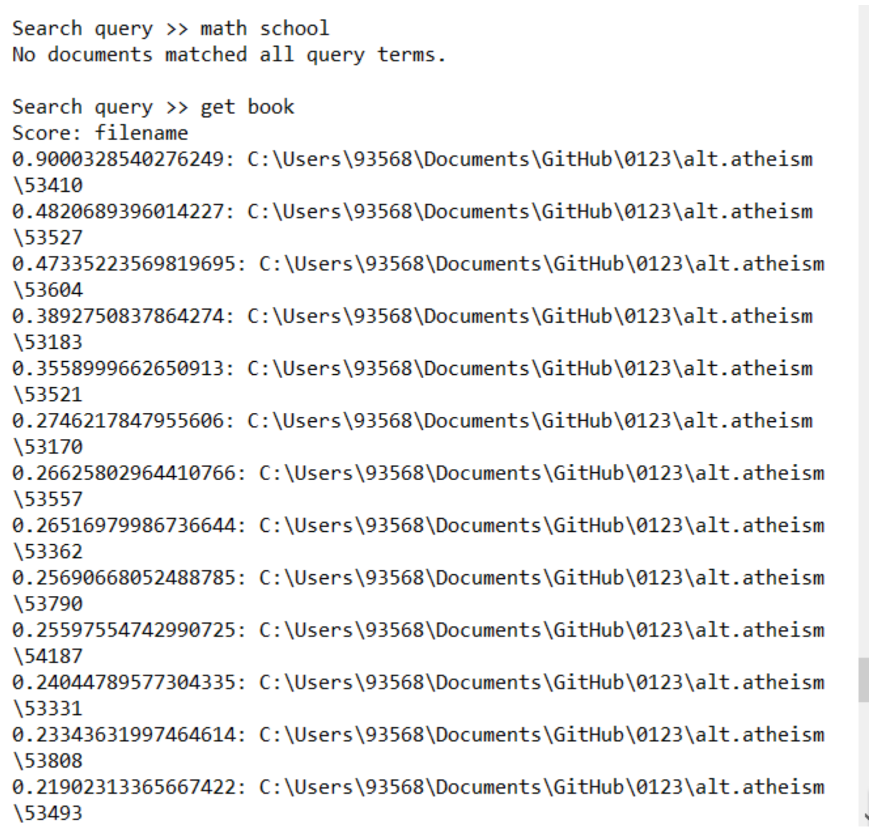
>>>增加查询功能：

根据用户输入的单词或一句话或一段话，对其预处理后在已有的向量空间模型中进行相似度查询（类似于搜索引擎的网页搜索），然后返回最为相似的文档，根据相似值降序排列，相关核心代码如下：



```
def do_search():

    query = tokenize(input("Search query >> "))
    if query == []:
        sys.exit()
    # find document ids containing all query terms.  Works by
    # intersecting the posting lists for all query terms.
    relevant_document_ids = intersection(
            [set(postings[term].keys()) for term in query])
    if not relevant_document_ids:
        print ("No documents matched all query terms.")
    else:
        scores = sorted([(id,similarity(query,id))
                          for id in relevant_document_ids],
                        key=lambda x: x[1],
                        reverse=True)
        print ("Score: filename")
        for (id,score) in scores:
            print (str(score)+": "+document_filenames[id])

def intersection(sets):

    return reduce(set.intersection, [s for s in sets])

def similarity(query,id):

    similarity = 0.0
    for term in query:
        if term in dictionary:
            similarity += inverse_document_frequency(term)*imp(term,id)
    similarity = similarity / length[id]
    return similarity
```

小样本数据测试结果如下：



```
Search query >> math school
No documents matched all query terms.

Search query >> get book
Score: filename
0.9000328540276249: C:\Users\93568\Documents\GitHub\0123\alt.atheism
\53410
0.4820689396014227: C:\Users\93568\Documents\GitHub\0123\alt.atheism
\53527
0.47335223569819695: C:\Users\93568\Documents\GitHub\0123\alt.atheism
\53604
0.3892750837864274: C:\Users\93568\Documents\GitHub\0123\alt.atheism
\53183
0.3558999662650913: C:\Users\93568\Documents\GitHub\0123\alt.atheism
\53521
0.2746217847955606: C:\Users\93568\Documents\GitHub\0123\alt.atheism
\53170
0.26625802964410766: C:\Users\93568\Documents\GitHub\0123\alt.atheism
\53557
0.26516979986736644: C:\Users\93568\Documents\GitHub\0123\alt.atheism
\53362
0.25690668052488785: C:\Users\93568\Documents\GitHub\0123\alt.atheism
\53790
0.25597554742990725: C:\Users\93568\Documents\GitHub\0123\alt.atheism
\54187
0.24044789577304335: C:\Users\93568\Documents\GitHub\0123\alt.atheism
\53331
0.23343631997464614: C:\Users\93568\Documents\GitHub\0123\alt.atheism
\53808
0.21902313365667422: C:\Users\93568\Documents\GitHub\0123\alt.atheism
\53493
```

四、9.27 后的版本改进

1、 改进 TF 的算法

先前版本使用如下公式：

对于在某一特定文件里的词语来说，它的重要性（词频 term frequency，TF）可表示为：

$$\mathrm{tf_{i,j}} = \frac{n_{i,j}}{\sum_k n_{k,j}}$$

- 分子是该词在文件中的出现次数
- 分母是在文件中所有字词的出现次数之和

改进后采用如下公式：

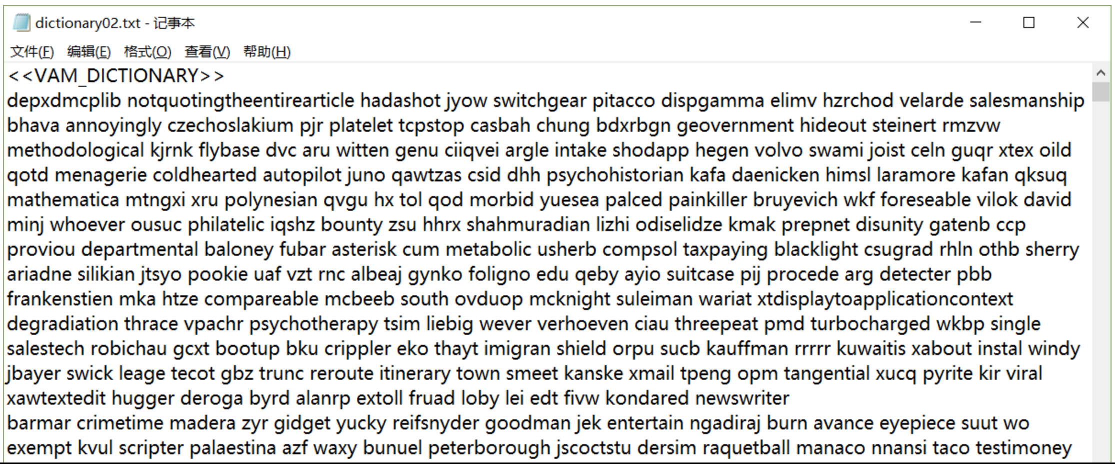
Sub-linear TF scaling

$$- \ tf(t,d) = \begin{cases} 1 + \log c(t,d), if \ c(t,d) > 0 \\ 0, otherwise \end{cases}$$

2、 改进单词的预处理，使用 textblob 工具包：

```
document=document.lower()
#document=re.sub(r'', " ",document)
document=re.sub(r"\W|\d|_|\s{2,}"," ",document)
terms=TextBlob(document).words.singularize()

result=[]
for word in terms:
    expected_str = Word(word)
    expected_str = expected_str.lemmatize("v")
    result.append(expected_str)
return result
```

而后打印出整个词典如下，整体比之前小了很多，875k→728k，而且由于进行了单复数和动词形式的规整，更加规范了一些；最后对整个词典还进行调整优化，将尾部词频较少的单词从词典中删除：


dictionary02.txt - 记事本
文件(F) 编辑(E) 格式(O) 查看(V) 帮助(H)

```
<<VAM_DICTIONARY>>
depxdmcplib notquotingtheentirearticle hadashot jyow switchgear pitacco dispgamma elimv hzrchod velarde salesmanship
bhava annoyingly czechoslakium pjr platelet tcpstop casbah chung bdxrbgn geovernment hideout steinert rmzvw
methodological kjrnk flybase dvc aru witten genu ciiqvei argle intake shodapp hegen volvo swami joist celn guqr xtex oild
qotd menagerie coldhearted autopilot juno qawtzas csid dhh psychohistorian kafa daenicken himsl laramore kafan qksuq
mathematica mtngxi xru polynesian qvgu hx tol qod morbid yuesea palced painkiller bruyevich wkf foreseable vilok david
minj whoever ousuc philatelic iqshz bounty zsu hhrx shahmuradian lizhi odiselidze kmak prepnet disunity gatenb ccp
proviou departmental baloney fubar asterisk cum metabolic usherb compsol taxpaying blacklight csugrad rhln othb sherry
ariadne silikian jtsyo pookie uaf vzt rnc albeaj gynko foligno edu qeby ayio suitcase pij procede arg detecter pbb
frankenstien mka htze compareable mcbeeb south ovduop mcknight suleiman wariat xtdisplaytoapplicationcontext
degradiation thrace vpachr psychotherapy tsim liebig wever verhoeven ciau threepeat pmd turbocharged wkbp single
salestech robichau gcxt bootup bku crippler eko thayt imigran shield orpu sucb kauffman rrrrr kuwaitis xabout instal windy
jbayer swick leage tecot gbz trunc reroute itinerary town smeet kanske xmail tpeng opm tangential xucq pyrite kir viral
xawtextedit hugger deroga byrd alanrp extoll fruad loby lei edt fivw kondared newswriter
barmar crimetime madera zyr gidget yucky reifsnyder goodman jek entertain ngadiraj burn avance eyepiece suut wo
exempt kvul scripter palaestina azf waxy bunuel peterborough jscoctstu dersim raquetball manaco nnansi taco testimoney
```

结论分析与体会：

向量空间模型基本实现，并且能在模型基础上进行一些基本的应用测试，但由于对于文档的处理完全都是有编写的函数完成，入对单词的单复数、形式等未能处理好，还有对于过于低频和高频的用处不大的单词未处理，都有待优化。