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Text Mining the Complete Works of William Shakespeare

September 5, 2013
By andrew

(This article was first published on **Exegetic Analytics » R**, and kindly contributed to R-bloggers)

I am starting a new project that will require some serious text mining. So, in the interests of bringing myself up to speed on the tm package, I thought I would apply it to the Complete Works of William Shakespeare and just see what falls out.

The first order of business was getting my hands on all that text. Fortunately it is available from a number of sources. I chose to use Project Gutenberg.

```
> TEXTFILE = "data/pg100.txt"
> if (!file.exists(TEXTFILE)) {
+     download.file("http://www.gutenberg.org/cache/
+ }
> shakespeare = readLines(TEXTFILE)
> length(shakespeare)
[1] 124787
```

That’s quite a solid chunk of data: 124787 lines. Let’s take a closer look.

```
> head(shakespeare)
[1] "The Project Gutenberg EBook of The Complete Wor
[2] "William Shakespeare"
[3] ""
[4] "This eBook is for the use of anyone anywhere at
[5] "almost no restrictions whatsoever.  You may cop
[6] "re-use it under the terms of the Project Gutenb
> tail(shakespeare)
[1] "http://www.gutenberg.org/2/4/6/8/24689"     ""
[3] "An alternative method of locating eBooks:" "htt
[5] ""                                           "***
```

There seems to be some header and footer text. We will want to get rid of that! Using a text editor I checked to see how many lines were occupied with metadata and then removed them before concatenating all of the lines into a single long, long, long string.

```
> shakespeare = shakespeare[-(1:173)]
> shakespeare = shakespeare[-(124195:length(shakespe
>
> shakespeare = paste(shakespeare, collapse = " ")
> nchar(shakespeare)
[1] 5436541
```

While I had the text open in the editor I noticed that sections in the document were separated by the following text:

```
<<THIS ELECTRONIC VERSION OF THE COMPLETE WORKS OF W
SHAKESPEARE IS COPYRIGHT 1990-1993 BY WORLD LIBRARY,
PROVIDED BY PROJECT GUTENBERG ETEXT OF ILLINOIS BENE
WITH PERMISSION.  ELECTRONIC AND MACHINE READABLE CO
DISTRIBUTED SO LONG AS SUCH COPIES (1) ARE FOR YOUR
PERSONAL USE ONLY, AND (2) ARE NOT DISTRIBUTED OR US
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SERVICE THAT CHARGES FOR DOWNLOAD TIME OR FOR MEMBER
```

Obviously that is going to taint the analysis. But it also serves as a convenient marker to divide that long, long, long string into separate documents.

```
> shakespeare = strsplit(shakespeare, "<<[^>]*>>")[[
> length(shakespeare)
[1] 218
```

This left me with a list of 218 documents. On further inspection, some of them appeared to be a little on the short side (in my limited experience, the bard is not known for brevity). As it turns out, the short documents were the dramatis personae for his plays. I removed them as well.

```
> (dramatis.personae <- grep("Dramatis Personae", sh
 [1]   2   8  11  17  23  28  33  43  49  55  62  68
[28] 164 170 176 182 188 194 200 206 212
> length(shakespeare)
[1] 218
> shakespeare = shakespeare[-dramatis.personae]
> length(shakespeare)
[1] 182
```

Down to 182 documents, each of which is a complete work.

The next task was to convert these documents into a corpus.

```
> library(tm)
>
> doc.vec <- VectorSource(shakespeare)
> doc.corpus <- Corpus(doc.vec)
> summary(doc.corpus)
A corpus with 182 text documents

The metadata consists of 2 tag-value pairs and a dat
Available tags are:
  create_date creator
Available variables in the data frame are:
  MetaID
```

There is a lot of information in those documents which is not particularly useful for text mining. So before proceeding any further, we will clean things up a bit. First we convert all of the text to lowercase and then remove punctuation, numbers and common English stopwords. Possibly the list of English stop words is not entirely appropriate for Shakespearean English, but it is a reasonable starting point.

```
> doc.corpus <- tm_map(doc.corpus, tolower)
> doc.corpus <- tm_map(doc.corpus, removePunctuation
> doc.corpus <- tm_map(doc.corpus, removeNumbers)
> doc.corpus <- tm_map(doc.corpus, removeWords, stop
```

Next we perform stemming, which removes affixes from words (so, for example, “run”, “runs” and “running” all become “run”).

```
> library(SnowballC)
>
> doc.corpus <- tm_map(doc.corpus, stemDocument)
```

All of these transformations have resulted in a lot of whitespace, which is then removed.

```
> doc.corpus <- tm_map(doc.corpus, stripWhitespace)
```

If we have a look at what’s left, we find that it’s just the lowercase, stripped down version of the text (which I have truncated here).

```
> inspect(doc.corpus[8])
A corpus with 1 text document

The metadata consists of 2 tag-value pairs and a dat
Available tags are:
  create_date creator
Available variables in the data frame are:
  MetaID

[[1]]
 act ii scene messina pompey hous enter pompey menec
 assist deed justest men menecr know worthi pompey d
 sue menecr ignor beg often harm wise powr deni us g
 peopl love sea mine power crescent augur hope say w
 will make war without door caesar get money lose he
```

This is where things start to get interesting. Next we create a Term Document Matrix (TDM) which reflects the number of times each word in the corpus is found in each of the documents.

```
> TDM <- TermDocumentMatrix(doc.corpus)
> TDM
A term-document matrix (18651 terms, 182 documents)

Non-/sparse entries: 182898/3211584
Sparsity           : 95%
Maximal term length: 31
Weighting          : term frequency (tf)
> inspect(TDM[1:10,1:10])
A term-document matrix (10 terms, 10 documents)

Non-/sparse entries: 1/99
Sparsity           : 99%
Maximal term length: 9
Weighting          : term frequency (tf)

           Docs
Terms        1 2 3 4 5 6 7 8 9 10
  aaron      0 0 0 0 0 0 0 0 0  0
  abaissiez  0 0 0 0 0 0 0 0 0  0
  abandon    0 0 0 0 0 0 0 0 0  0
  abandond   0 1 0 0 0 0 0 0 0  0
  abas       0 0 0 0 0 0 0 0 0  0
  abashd     0 0 0 0 0 0 0 0 0  0
  abat       0 0 0 0 0 0 0 0 0  0
  abatfowl   0 0 0 0 0 0 0 0 0  0
  abbess     0 0 0 0 0 0 0 0 0  0
  abbey      0 0 0 0 0 0 0 0 0  0
```

The extract from the TDM shows, for example, that the word “abandond” occurred once in document number 2 but was not present in any of the other first ten documents. We could have generated the transpose of the DTM as well.

```
> DTM <- DocumentTermMatrix(doc.corpus)
> inspect(DTM[1:10,1:10])
A document-term matrix (10 documents, 10 terms)

Non-/sparse entries: 1/99
Sparsity           : 99%
Maximal term length: 9
Weighting          : term frequency (tf)

    Terms
Docs aaron abaissiez abandon abandond abas abashd ab
  1      0         0       0        0    0      0
  2      0         0       0        1    0      0
  3      0         0       0        0    0      0
  4      0         0       0        0    0      0
  5      0         0       0        0    0      0
  6      0         0       0        0    0      0
  7      0         0       0        0    0      0
  8      0         0       0        0    0      0
  9      0         0       0        0    0      0
  10     0         0       0        0    0      0
```

Which of these proves to be most convenient will depend on the relative number of documents and terms in your data.

Now we can start asking questions like: what are the most frequently occurring terms?

```
> findFreqTerms(TDM, 2000)
 [1] "come"   "enter"  "good"   "king"   "let"    "lord"
[14] "thi"    "thou"   "well"   "will"
```

Each of these words occurred more that 2000 times.

What about associations between words? Let’s have a look at what other words had a high association with “love”.

```
> findAssocs(TDM, "love", 0.8)
beauti     eye
  0.83    0.80
```

Well that’s not too surprising!

From our first look at the TDM we know that there are many terms which do not occur very often. It might make sense to simply remove these sparse terms from the analysis.

```
> TDM.common = removeSparseTerms(TDM, 0.1)
> dim(TDM)
[1] 18651   182
> dim(TDM.common)
[1]  71 182
```

From the 18651 terms that we started with, we are now left with a TDM which considers on 71 commonly occurring terms.

```
> inspect(TDM.common[1:10,1:10])
A term-document matrix (10 terms, 10 documents)

Non-/sparse entries: 94/6
Sparsity           : 6%
Maximal term length: 6
Weighting          : term frequency (tf)

        Docs
Terms     1 2  3  4  5  6  7  8 9 10
  act     1 4  7  9  6  3  2 14 1  0
  art    53 0  9  3  5  3  2 17 0  6
  away   18 5  8  4  2 10  5 13 1  7
  call   17 1  4  2  2  1  6 17 3  7
  can    44 8 12  5 10  6 10 24 1  5
  come   19 9 16 17 12 15 14 89 9 15
  day    43 2  2  4  1  5  3 17 2  3
  enter   0 7 12 11 10 10 14 87 4  6
  exeunt  0 3  8  8  5  4  7 49 1  4
  exit    0 6  8  5  6  5  3 31 3  2
```

Finally we are going to put together a visualisation. The TDM is stored as a sparse matrix. This was an apt representation for the initial TDM, but the reduced TDM containing only frequently occurring words is probably better stored as a normal matrix. We'll make the conversion and see.

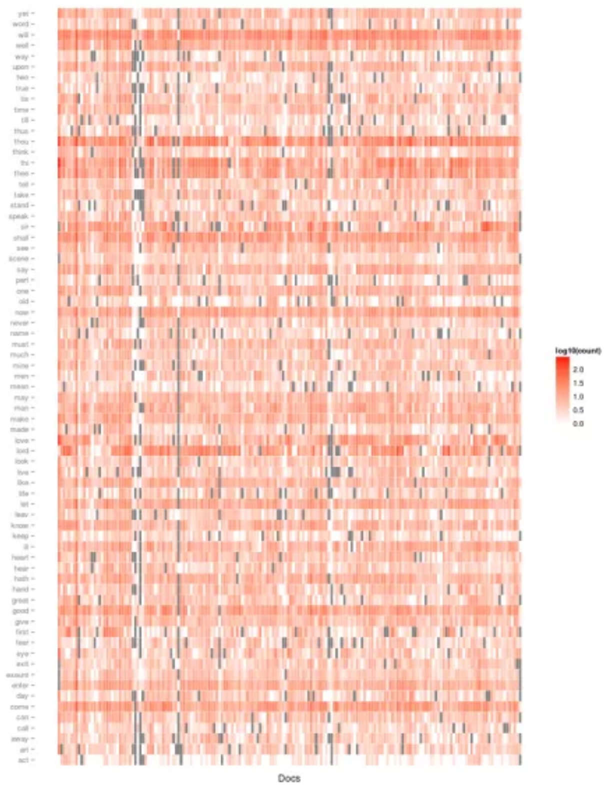
```
> library(slam)
>
> TDM.dense <- as.matrix(TDM.common)
>
> TDM.dense
> object.size(TDM.common)
207872 bytes
> object.size(TDM.dense)
112888 bytes
```

So, as it turns out the sparse representation was actually wasting space! (This will generally not be true though: it will only apply for a matrix consisting of just the common terms). Anyway, we need the data as a normal matrix in order to produce the visualisation. The next step is to convert it into a tidy format.

```
> library(reshape2)
>
> TDM.dense = melt(TDM.dense, value.name = "count")
> head(TDM.dense)
  Terms Docs count
1   act    1     1
2   art    1    53
3  away    1    18
4  call    1    17
5   can    1    44
6  come    1    19
```

And finally generate the visualisation.

```
> library(ggplot2)
>
> ggplot(TDM.dense, aes(x = Docs, y = Terms, fill =
+     geom_tile(colour = "white") +
+     scale_fill_gradient(high="#FF0000" , low="#FFF
+     ylab("") +
+     theme(panel.background = element_blank()) +
+     theme(axis.text.x = element_blank(), axis.tick
```



The colour scale indicates the number of times that each of the terms cropped up in each of the documents. I applied a logarithmic transform to the counts since there was a very large disparity in the numbers across terms and documents. The grey tiles correspond to terms which are not found in the corresponding document.

One can see that some terms, like “will” turn up frequently in most documents, while “love” is common in some and rare or absent in others.

That was interesting. Not sure that I would like to make any conclusions on the basis of the results above (Shakespeare is well outside my field of expertise!), but I now have a pretty good handle on how the tm package works. As always, feedback will be appreciated!

References

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- Feinerer, I. (2013). Introduction to the tm Package: Text Mining in R.
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