Text Mining with R *

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R and Data Mining Course
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* Chapter 10: Text Mining, in *R and Data Mining: Examples and Case Studies*. http://www.rdatamining.com/docs/RDataMining-book.pdf

Contents

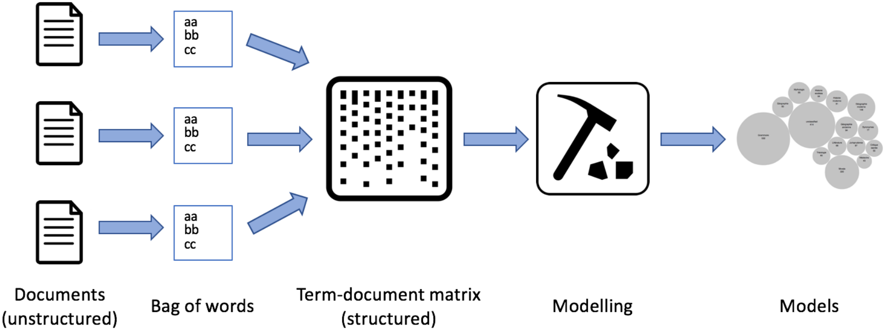
Text Data

- Text documents in a natural language
- Unstructured
- Documents in plain text, Word or PDF format
- Emails, online chat logs and phone transcripts
- Online news and forums, blogs, micro-blogs and social media
- . . .

Typical Process of Text Mining

1. Transform text into structured data
    - Term-Document Matrix (TDM)
    - Entities and relations
    - ...
2. Apply traditional data mining techniques to the above structured data
    - Clustering
    - Classification
    - Social Network Analysis (SNA)
    - ...

Typical Process of Text Mining (cont.)



Term-Document Matrix (TDM)

- Also known as Document-Term Matrix (DTM)
- A 2D matrix
- Rows: terms or words
- Columns: documents
- Entry $m_{i,j}$: number of occurrences of term t_i in document d_j
- Term weighting schemes: Term Frequency, Binary Weight, TF-IDF, etc.

TF-IDF

- Term Frequency (TF) $\mathrm{tf}_{i,j}$: the number of occurrences of term t_i in document d_j
- Inverse Document Frequency (IDF) for term t_i is:

$$\mathrm{idf}_i = \log_2 \frac{|D|}{|\{d \mid t_i \in d\}|} \tag{1}$$

  $|D|$: the total number of documents
  $|\{d \mid t_i \in d\}|$: the number of documents where term t_i appears
- Term Frequency - Inverse Document Frequency (TF-IDF)

$$\mathrm{tfidf} = \mathrm{tf}_{i,j} \cdot \mathrm{idf}_i \tag{2}$$

- IDF reduces the weight of terms that occur frequently in documents and increases the weight of terms that occur rarely.

An Example of TDM

Doc1: I like R.
Doc2: I like Python.

Term Frequency

	Doc1	Doc2
I	1	1
like	1	1
Python	0	1
R	1	0

IDF

	IDF
I	0
like	0
Python	1
R	1

TF-IDF

	Doc1	Doc2
I	0	0
like	0	0
Python	0	1
R	1	0

An Example of TDM

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I	0
like	0
Python	1
R	1

TF-IDF

	Doc1	Doc2
I	0	0
like	0	0
Python	0	1
R	1	0

Terms that can distinguish different documents are given greater weights.

An Example of TDM (cont.)

Doc1: I like R.
Doc2: I like Python.

Term Frequency

	Doc1	Doc2
I	1	1
like	1	1
Python	0	1
R	1	0

IDF

	IDF
I	0
like	0
Python	1
R	1

Normalized Term Frequency

	Doc1	Doc2
I	0.33	0.33
like	0.33	0.33
Python	0	0.33
R	0.33	0

Normalized TF-IDF

	Doc1	Doc2
I	0	0
like	0	0
Python	0	0.33
R	0.33	0

An Example of Term Weighting in R

```r
library(magrittr)
library(tm) ## package for text mining
a <- c("I like R", "I like Python")
## build corpus
b <- a %>% VectorSource() %>% Corpus()
## build term document matrix
m <- b %>% TermDocumentMatrix(control=list(wordLengths=c(1, Inf)))
m %>% inspect()
## various term weighting schemes
m %>% weightBin() %>% inspect() ## binary weighting
m %>% weightTf() %>% inspect() ## term frequency
m %>% weightTfIdf(normalize=F) %>% inspect() ## TF-IDF
m %>% weightTfIdf(normalize=T) %>% inspect() ## normalized TF-IDF
```

More options provided in package *tm*:

- `weightSMART`
- `WeightFunction`

Text Mining Tasks

- Text classification
- Text clustering and categorization
- Topic modelling
- Sentiment analysis
- Document summarization
- Entity and relation extraction
- ...

Topic Modelling

- To identify topics in a set of documents
- It groups both documents that use similar words and words that occur in a similar set of documents.
- Intuition: Documents related to R would contain more words like R, ggplot2, plyr, stringr, knitr and other R packages, than Python related keywords like Python, NumPy, SciPy, Matplotlib, etc.
- A document can be of multiple topics in different proportions. For instance, a document can be 90% about R and 10% about Python. $\Rightarrow$ soft/fuzzy clustering
- Latent Dirichlet Allocation (LDA): the most widely used topic model

Sentiment Analysis

- Also known as opinion mining
- To determine attitude, polarity or emotions from documents
- Polarity: positive, negative, netural
- Emotions: angry, sad, happy, bored, afraid, etc.
- Method:
    1. identify invidual words and phrases and map them to different emotional scales
    2. adjust the sentiment value of a concept based on modifications surrounding it

Document Summarization

- To create a summary with major points of the orignial document
- Approaches
  - Extraction: select a subset of existing words, phrases or sentences to build a summary
  - Abstraction: use natural language generation techniques to build a summary that is similar to natural language

Entity and Relationship Extraction

- Named Entity Recognition (NER): identify named entities in text into pre-defined categories, such as person names, organizations, locations, date and time, etc.
- Relationship Extraction: identify associations among entities
- Example:
  Ben lives at 5 Geroge St, Sydney.

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  Ben lives at 5 Geroge St, Sydney.

Ben → 5 Geroge St, Sydney

Contents

Twitter

- An online social networking service that enables users to send and read short 280-character (used to be 140 before November 2017) messages called “tweets” (Wikipedia)
- Over 300 million monthly active users (as of 2018)
- Creating over 500 million tweets per day

RDataMining Twitter Account

Yanchang Zhao
@RDataMining

Tweets	Following	Followers	Likes	Lists	Moments
748	85	3,332	17	0	0

Edit profile

@RDataMining

R and Data Mining. Group on LinkedIn: group.rdatamining.com

Australia

RDataMining.com

Joined April 2011

Photos and videos

Your Tweet activity

Your Tweets earned **3,421 impressions** over the last **28 days**

Yanchang Zhao @RDataMining · Nov 26

I will deliver a tutorial on R and Data Mining at the AusDM 2018 Conference, in Bathurst, Australia on 29 November 2018. Slides, script and data for the tutorial are available at rdatamining.com/training/ausdm…

2 2

Yanchang Zhao @RDataMining · Nov 14

New webinar: 10 Guidelines for A/B Testing

Discover 10 best practices that will help you avoid common A/B testing pitfalls with Emily Robinson, a data scientist at DataCamp.

Registration link: attendee.gotowebinar.com/register/84237…

1

Yanchang Zhao @RDataMining · Nov 7

Research Scientist in Data Science - 2 Positions at Data61, CSIRO. Application close on 28 November 2018. jobs.csiro.au/job/Melbourne%…

1

Process

1. Extract tweets and followers from the Twitter website with R and the *twitteR* package
2. With the *tm* package, clean text by removing punctuations, numbers, hyperlinks and stop words, followed by stemming and stem completion
3. Build a term-document matrix
4. Cluster Tweets with text clustering
5. Analyse topics with the *topicmodels* package
6. Analyse sentiment with the *sentiment140* package
7. Analyse following/followed and retweeting relationships with the *igraph* package

Retrieve Tweets

```r
## Option 1: retrieve tweets from Twitter
library(twitteR)
library(ROAuth)
## Twitter authentication
setup_twitter_oauth(consumer_key, consumer_secret, access_token, access
## 3200 is the maximum to retrieve
tweets <- "RDataMining" %>% userTimeline(n = 3200)
```

See details of *Twitter Authentication with OAuth* in Section 3 of `http://geoffjentry.hexdump.org/twitteR.pdf`.

```r
## Option 2: download @RDataMining tweets from RDataMining.com
library(twitteR)
url <- "http://www.rdatamining.com/data/RDataMining-Tweets-20160212.rds
download.file(url, destfile = "./data/RDataMining-Tweets-20160212.rds")
## load tweets into R
tweets <- readRDS("./data/RDataMining-Tweets-20160212.rds")
```

```r
(n.tweet <- tweets %>% length())
## [1] 448

# convert tweets to a data frame
tweets.df <- tweets %>% twListToDF()
# tweet #1
tweets.df[1, c("id", "created", "screenName", "replyToSN",
  "favoriteCount", "retweetCount", "longitude", "latitude", "text")]
##                   id             created  screenName replyToSN
## 1 697031245503418368 2016-02-09 12:16:13 RDataMining      <NA>
##   favoriteCount retweetCount longitude latitude
## 1            13           14        NA       NA
##                                                               ...
## 1 A Twitter dataset for text mining: @RDataMining Tweets ex...

# print tweet #1 and make text fit for slide width
tweets.df$text[1] %>% strwrap(60) %>% writeLines()
## A Twitter dataset for text mining: @RDataMining Tweets
## extracted on 3 February 2016. Download it at
## https://t.co/lQp94IvfPf
```

Text Cleaning Functions

- Convert to lower case: `tolower`
- Remove punctuation: `removePunctuation`
- Remove numbers: `removeNumbers`
- Remove URLs
- Remove stop words (like 'a', 'the', 'in'): `removeWords`, `stopwords`
- Remove extra white space: `stripWhitespace`

```
library(tm)
# function for removing URLs, i.e.,
#  "http" followed by any non-space letters
removeURL <- function(x) gsub("http[^[:space:]]*", "", x)
# function for removing anything other than English letters or space
removeNumPunct <- function(x) gsub("[^[:alpha:][:space:]]*", "", x)
# customize stop words
myStopwords <- c(setdiff(stopwords('english'), c("r", "big")),
                 "use", "see", "used", "via", "amp")
```

See details of regular expressions by running `?regex` in R console.

Text Cleaning

```r
# build a corpus and specify the source to be character vectors
corpus.raw <- tweets.df$text %>% VectorSource() %>% Corpus()

# text cleaning
corpus.cleaned <- corpus.raw %>%
  # convert to lower case
  tm_map(content_transformer(tolower)) %>%
  # remove URLs
  tm_map(content_transformer(removeURL)) %>%
  # remove numbers and punctuations
  tm_map(content_transformer(removeNumPunct)) %>%
  # remove stopwords
  tm_map(removeWords, myStopwords) %>%
  # remove extra whitespace
  tm_map(stripWhitespace)
```

Stemming and Stem Completion [†]

```r
## stem words
corpus.stemmed <- corpus.cleaned %>% tm_map(stemDocument)

## stem completion
stemCompletion2 <- function(x, dictionary) {
  x <- unlist(strsplit(as.character(x), " "))
  x <- x[x != ""]
  x <- stemCompletion(x, dictionary=dictionary)
  x <- paste(x, sep="", collapse=" ")
  stripWhitespace(x)
}

corpus.completed <- corpus.stemmed %>%
  lapply(stemCompletion2, dictionary=corpus.cleaned) %>%
  VectorSource() %>% Corpus()
```

[†] http://stackoverflow.com/questions/25206049/stemcompletion-is-not-working

Before/After Text Cleaning and Stemming

```
# original text
corpus.raw[[1]]$content %>% strwrap(60) %>% writeLines()
## A Twitter dataset for text mining: @RDataMining Tweets
## extracted on 3 February 2016. Download it at
## https://t.co/lQp94IvfPf

# after basic cleaning
corpus.cleaned[[1]]$content %>% strwrap(60) %>% writeLines()
## twitter dataset text mining rdatamining tweets extracted
## february download

# stemmed text
corpus.stemmed[[1]]$content %>% strwrap(60) %>% writeLines()
## twitter dataset text mine rdatamin tweet extract februari
## download

# after stem completion
corpus.completed[[1]]$content %>% strwrap(60) %>% writeLines()
## twitter dataset text miner rdatamining tweet extract
## download
```

Issues in Stem Completion: "Miner" vs "Mining"

```r
# count word frequence
wordFreq <- function(corpus, word) {
  results <- lapply(corpus,
    function(x) grep(as.character(x), pattern=paste0("\\<",word)) )
  sum(unlist(results))
}
n.miner <- corpus.cleaned %>% wordFreq("miner")
n.mining <- corpus.cleaned %>% wordFreq("mining")
cat(n.miner, n.mining)
## 9 104

# replace old word with new word
replaceWord <- function(corpus, oldword, newword) {
  tm_map(corpus, content_transformer(gsub),
         pattern=oldword, replacement=newword)
}
corpus.completed <- corpus.completed %>%
  replaceWord("miner", "mining") %>%
  replaceWord("universidad", "university") %>%
  replaceWord("scienc", "science")
```

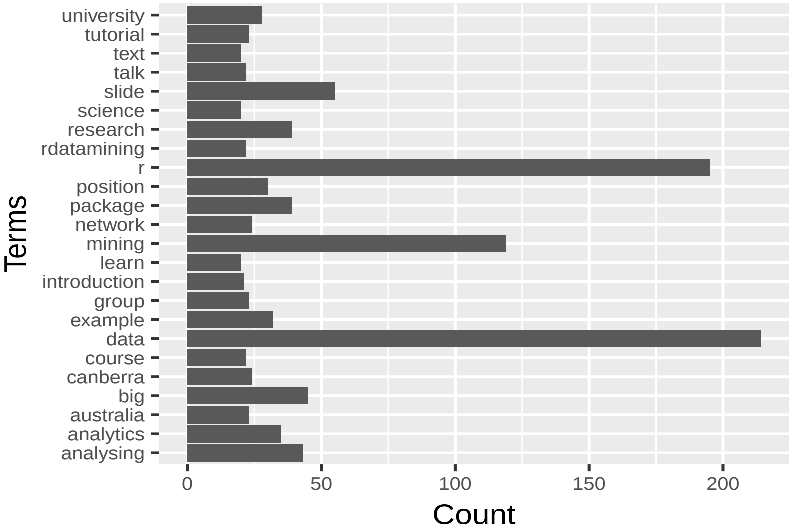
Build Term Document Matrix

```r
tdm <- corpus.completed %>%
  TermDocumentMatrix(control = list(wordLengths = c(1, Inf)))  %>%
  print
## <<TermDocumentMatrix (terms: 1073, documents: 448)>>
## Non-/sparse entries: 3594/477110
## Sparsity           : 99%
## Maximal term length: 23
## Weighting          : term frequency (tf)

idx <- which(dimnames(tdm)$Terms %in% c("r", "data", "mining"))
tdm[idx, 21:30] %>% as.matrix()
##           Docs
## Terms     21 22 23 24 25 26 27 28 29 30
##   mining   0  0  0  0  1  0  0  0  0  1
##   data     0  1  0  0  1  0  0  0  0  1
##   r        1  1  1  1  0  1  0  1  1  1
```

Top Frequent Terms

```r
# inspect frequent words
freq.terms <- tdm %>% findFreqTerms(lowfreq = 20) %>% print
##  [1] "mining"       "rdatamining"  "text"         "analytics"
##  [5] "australia"    "data"         "canberra"     "group"
##  [9] "university"   "science"      "slide"        "tutorial"
## [13] "big"          "learn"        "package"      "r"
## [17] "network"      "course"       "introduction" "talk"
## [21] "analysing"    "research"     "position"     "example"

term.freq <- tdm %>% as.matrix() %>% rowSums()
term.freq <- term.freq %>% subset(term.freq >= 20)
df <- data.frame(term = names(term.freq), freq = term.freq)
```

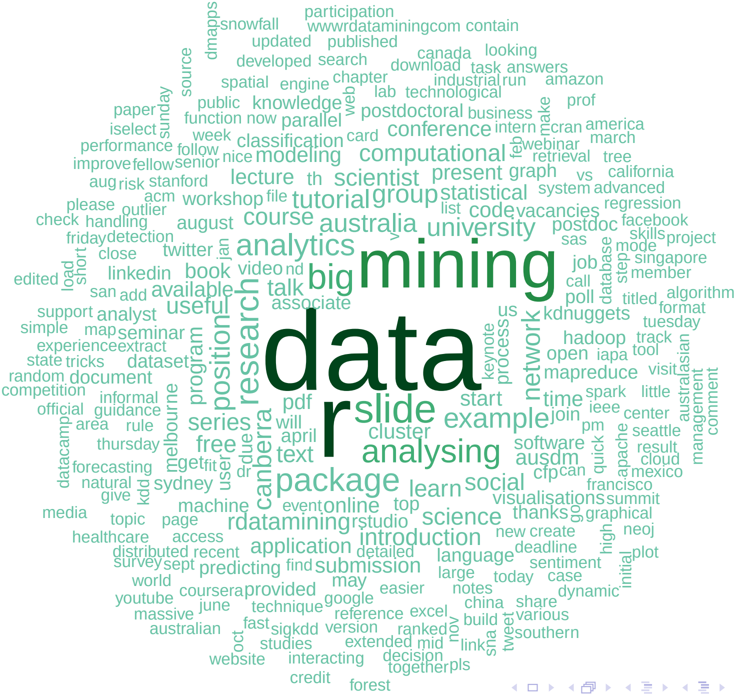
```
library(ggplot2)
ggplot(df, aes(x=term, y=freq)) + geom_bar(stat="identity") +
  xlab("Terms") + ylab("Count") + coord_flip() +
  theme(axis.text=element_text(size=7))
```



Wordcloud

```r
m <- tdm %>% as.matrix
# calculate the frequency of words and sort it by frequency
word.freq <- m %>% rowSums() %>% sort(decreasing = T)
# colors
library(RColorBrewer)
pal <- brewer.pal(9, "BuGn")[-(1:4)]
```

```r
# plot word cloud
library(wordcloud)
wordcloud(words = names(word.freq), freq = word.freq, min.freq = 3,
    random.order = F, colors = pal)
```

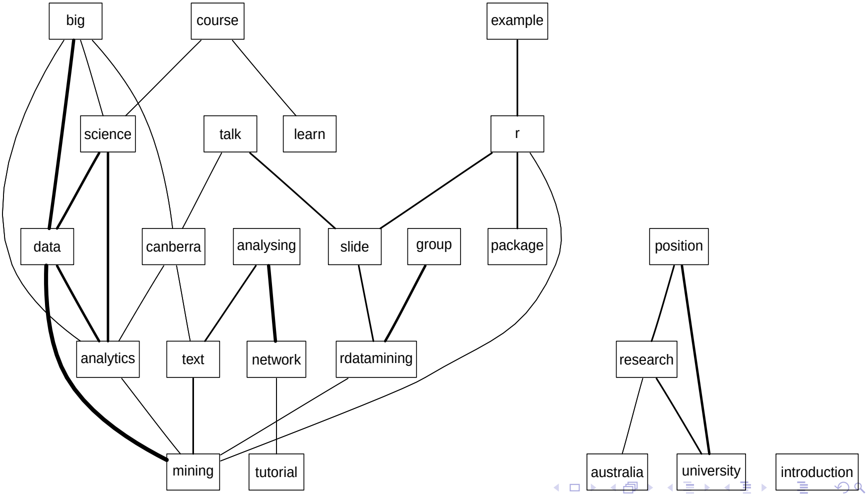

data
mining
r
slide
analysing
package
big
analytics
research
position
example
network
australia
university
group
tutorial
scientist
computational
conference
statistical
course
useful
talk
series
free
text
canberra
learn
social
science
introduction
rdatamining
online
application
submission
language
ausdm
software
time
start
cluster
pdf
will
april
program
melbourne
sydney
machine
predicting
provided
participation
snowfall
dmapps
wwwrdataminingcom
contain
updated
published
canada
looking
developed
search
download
task
answers
source
spatial
engine
chapter
industrial
run
amazon
sunday
lab
technological
public
knowledge
web
prof
paper
function
now
parallel
postdoctoral
business
make
iselect
week
card
intern
cran
america
performance
follow
classification
feb
webinar
march
improve
fellow
senior
nice
modeling
retrieval
tree
aug
risk
stanford
lecture
th
present
graph
vs
california
acm
file
system
advanced
please
outlier
workshop
list
code
vacancies
regression
check
handling
august
postdoc
facebook
friday
detection
skills
project
sas
mode
close
twitter
jan
job
singapore
database
step
member
edited
load
short
linkedin
book
video
nd
call
algorithm
san
add
available
associate
poll
titled
format
support
analyst
us
kdnuggets
tuesday
simple
map
seminar
hadoop
track
experience
extract
keynote
process
open
iapa
tool
state
tricks
dataset
visit
asian
random
document
mapreduce
competition
management
comment
informal
spark
little
australian
official
guidance
ieee
center
area
rule
join
pm
seattle
datacamp
thursday
result
get
fit
due
quick
apache
cloud
forecasting
user
dr
cfp
can
mexico
natural
kdd
give
francisco
visualisations
summit
media
event
top
thanks
go
graphical
topic
page
rstudio
healthcare
access
new
create
high
neoj
distributed
recent
deadline
survey
sept
detailed
plot
find
sentiment
initial
world
large
today
case
may
coursera
easier
notes
dynamic
youtube
google
june
china
share
technique
massive
reference
excel
build
various
fast
nov
australian
sigkdd
version
ranked
tweet
southern
oct
studies
extended
mid
link
sna
website
interacting
decision
together
pls
credit
forest

Associations

```r
# which words are associated with 'r'?
tdm %>% findAssocs("r", 0.2)
## $r
##     code  example   series     user markdown
##     0.27     0.21     0.21     0.20     0.20

# which words are associated with 'data'?
tdm %>% findAssocs("data", 0.2)
## $data
##    mining       big analytics   science      poll
##      0.48      0.44      0.31      0.29      0.24
```

Network of Terms

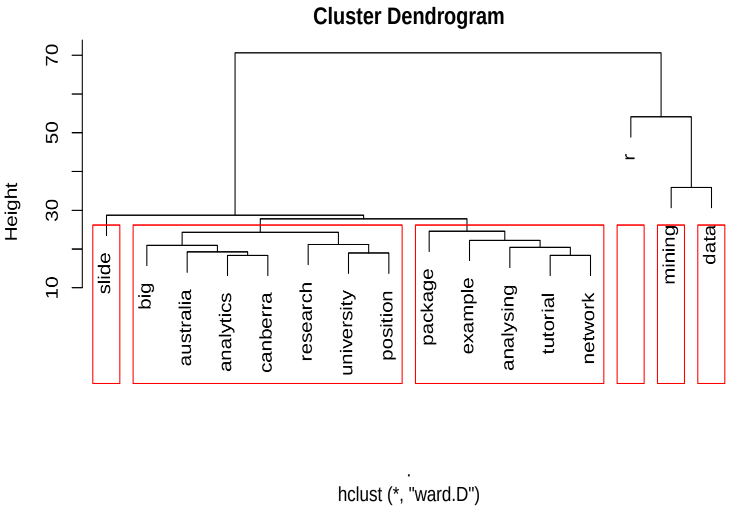
```r
library(graph)
library(Rgraphviz)
plot(tdm, term = freq.terms, corThreshold = 0.1, weighting = T)
```



Hierarchical Clustering of Terms

```r
# remove sparse terms
m2 <- tdm %>% removeSparseTerms(sparse = 0.95) %>% as.matrix()
# calculate distance matrix
dist.matrix <- m2 %>% scale() %>% dist()
# hierarchical clustering
fit <- dist.matrix %>% hclust(method = "ward")
```

```r
plot(fit)
fit %>% rect.hclust(k = 6)  # cut tree into 6 clusters
groups <- fit %>% cutree(k = 6)
```



```
m3 <- m2 %>% t()  # transpose the matrix to cluster documents
set.seed(122)  # set a fixed random seed to make the result reproducibl
k <- 6  # number of clusters
kmeansResult <- kmeans(m3, k)
round(kmeansResult$centers, digits = 3)  # cluster centers
```

```
##   mining analytics australia  data canberra university slide
## 1  0.435     0.000     0.000 0.217    0.000      0.000 0.087
## 2  1.128     0.154     0.000 1.333    0.026      0.051 0.179
## 3  0.055     0.018     0.009 0.164    0.027      0.009 0.227
## 4  0.083     0.014     0.056 0.000    0.035      0.097 0.090
## 5  0.412     0.206     0.098 1.196    0.137      0.039 0.078
## 6  0.167     0.133     0.133 0.567    0.033      0.233 0.000
##   tutorial   big package     r network analysing research
## 1    0.043 0.000   0.043 1.130   0.087     0.174    0.000
## 2    0.026 0.077   0.282 1.103   0.000     0.051    0.000
## 3    0.064 0.018   0.109 1.127   0.045     0.109    0.000
## 4    0.056 0.007   0.090 0.000   0.090     0.111    0.000
## 5    0.059 0.333   0.010 0.020   0.020     0.059    0.020
## 6    0.000 0.167   0.033 0.000   0.067     0.100    1.233
##   position example
## 1    0.000   1.043
## 2    0.000   0.026
## 3    0.000   0.000
## 4    0.076   0.035
```

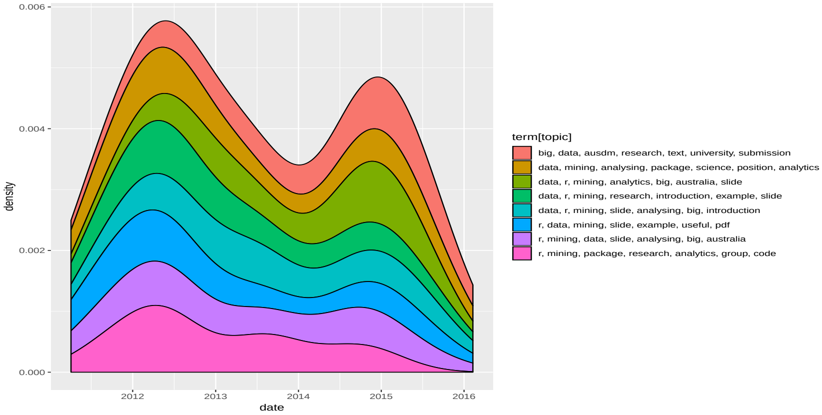
```
for (i in 1:k) {
    cat(paste("cluster ", i, ":  ", sep = ""))
    s <- sort(kmeansResult$centers[i, ], decreasing = T)
    cat(names(s)[1:5], "\n")
    # print the tweets of every cluster
    # print(tweets[which(kmeansResult$cluster==i)])
}
## cluster 1:  r example mining data analysing
## cluster 2:  data mining r package slide
## cluster 3:  r slide data package analysing
## cluster 4:  analysing university slide package network
## cluster 5:  data mining big analytics canberra
## cluster 6:  research data position university mining
```

Topic Modelling

```
dtm <- tdm %>% as.DocumentTermMatrix()
library(topicmodels)
lda <- LDA(dtm, k = 8)  # find 8 topics
term <- terms(lda, 7)  # first 7 terms of every topic
term <- apply(term, MARGIN = 2, paste, collapse = ", ") %>% print
##                                                                     To...
##           "r, mining, package, research, analytics, group, ...
##                                                                     To...
##              "data, r, mining, analytics, big, australia, s...
##                                                                     To...
##                   "r, data, mining, slide, example, useful,...
##                                                                     To...
##        "data, r, mining, research, introduction, example, s...
##                                                                     To...
## "data, mining, analysing, package, science, position, analy...
##                                                                     To...
##           "data, r, mining, slide, analysing, big, introduc...
##                                                                     To...
##       "big, data, ausdm, research, text, university, submis...
##                                                                     To...
##              "r, mining, data, slide, analysing, big, austr...
```

Topic Modelling

```
rdm.topics <- topics(lda) # 1st topic identified for every document (tw
rdm.topics <- data.frame(date=as.IDate(tweets.df$created),
                         topic=rdm.topics)
ggplot(rdm.topics, aes(date, fill = term[topic])) +
  geom_density(position = "stack")
```



Another way to plot steam graph:

http://menugget.blogspot.com.au/2013/12/data-mountains-and-streams-stacked-area.html

Sentiment Analysis

```r
# install package sentiment140
require(devtools)
install_github("sentiment140", "okugami79")
```

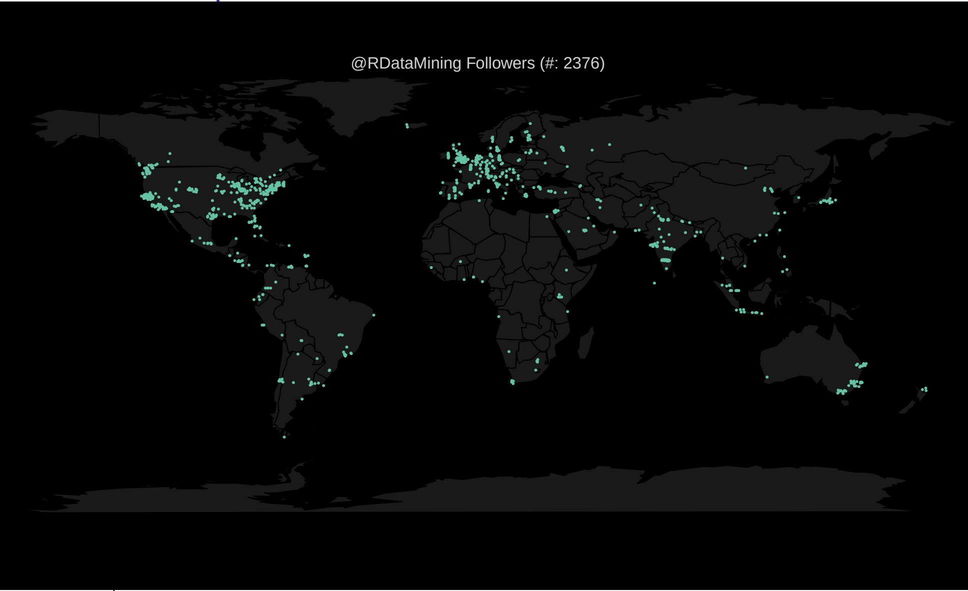
```r
# sentiment analysis
library(sentiment)
sentiments <- sentiment(tweets.df$text)
table(sentiments$polarity)
# sentiment plot
sentiments$score <- 0
sentiments$score[sentiments$polarity == "positive"] <- 1
sentiments$score[sentiments$polarity == "negative"] <- -1
sentiments$date <- as.IDate(tweets.df$created)
result <- aggregate(score ~ date, data = sentiments, sum)
```

Retrieve User Info and Followers

```
user <- getUser("RDataMining")
user$toDataFrame()
friends <- user$getFriends()  # who this user follows
followers <- user$getFollowers()  # this user's followers
followers2 <- followers[[1]]$getFollowers()  # a follower's followers
```

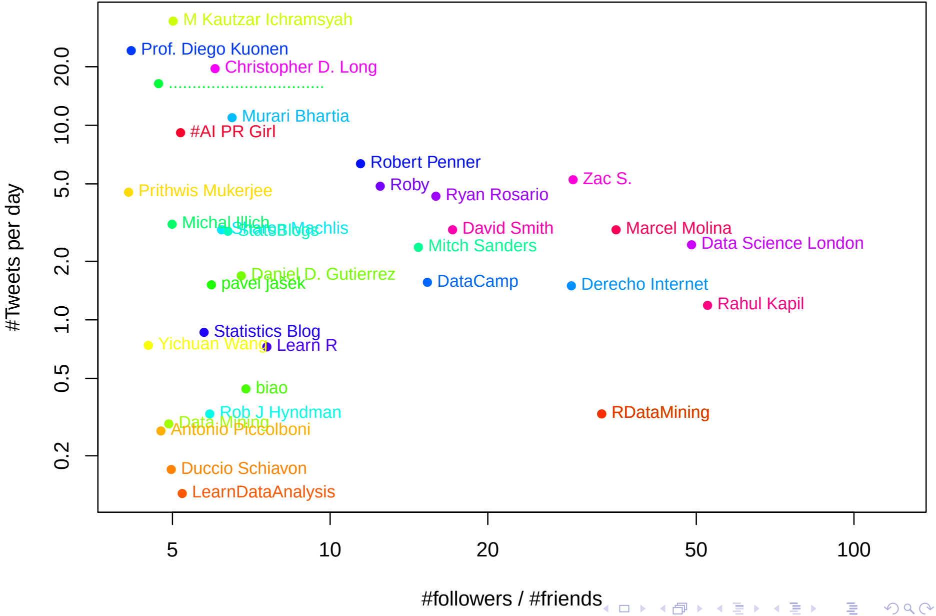
```
##                     [,1]                                    ...
## description         "R and Data Mining. Group on LinkedIn: ht...
## statusesCount       "583"                                   ...
## followersCount      "2376"                                  ...
## favoritesCount      "6"                                     ...
## friendsCount        "72"                                    ...
## url                 "http://t.co/LwL50uRmPd"                ...
## name                "Yanchang Zhao"                         ...
## created             "2011-04-04 09:15:43"                   ...
## protected           "FALSE"                                 ...
## verified            "FALSE"                                 ...
## screenName          "RDataMining"                           ...
## location            "Australia"                             ...
## lang                "en"                                    ...
## id                  "276895537"                             ...
```

Follower Map[‡]



[‡]Based on Jeff Leek's twitterMap function at
http://biostat.jhsph.edu/~jleek/code/twitterMap.R

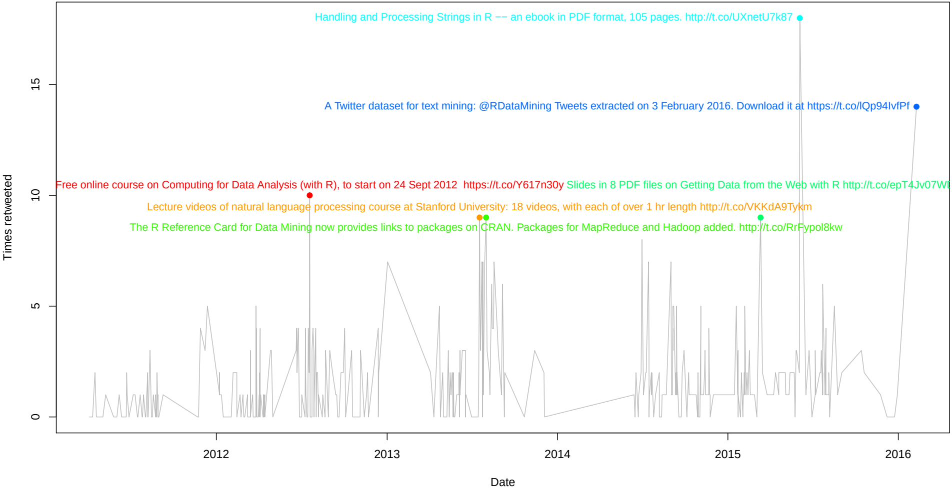
Active Influential Followers



Top Retweeted Tweets

```
# select top retweeted tweets
table(tweets.df$retweetCount)
selected <- which(tweets.df$retweetCount >= 9)

# plot them
dates <- strptime(tweets.df$created, format="%Y-%m-%d")
plot(x=dates, y=tweets.df$retweetCount, type="l", col="grey",
     xlab="Date", ylab="Times retweeted")
colors <- rainbow(10)[1:length(selected)]
points(dates[selected], tweets.df$retweetCount[selected],
       pch=19, col=colors)
text(dates[selected], tweets.df$retweetCount[selected],
     tweets.df$text[selected], col=colors, cex=.9)
```

Top Retweeted Tweets



Tracking Message Propagation

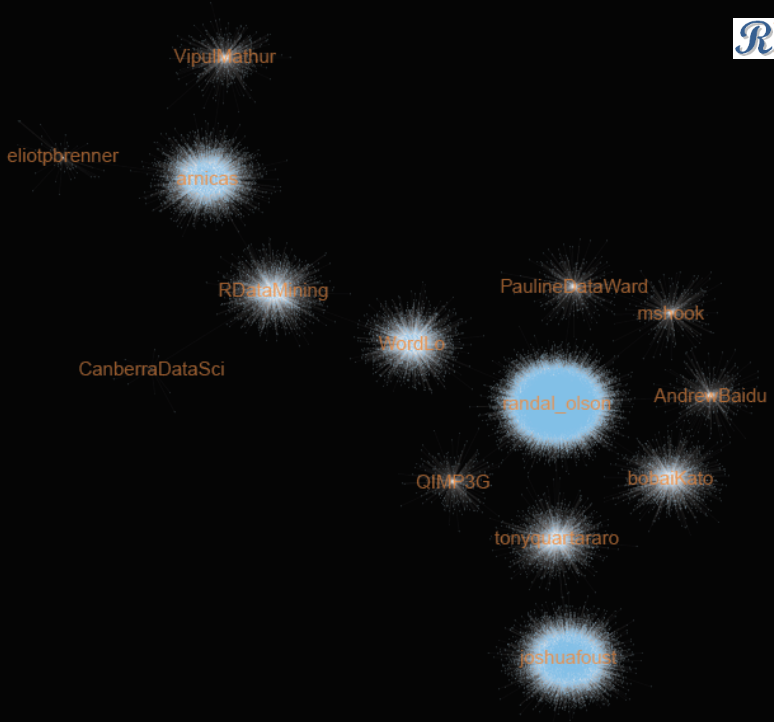
```r
tweets[[1]]
retweeters(tweets[[1]]$id)
retweets(tweets[[1]]$id)
```

```
## [1] "RDataMining: A Twitter dataset for text mining: @RData...
```

```
##  [1] "197489286"  "316875164"  "229796464"  "3316009302"
##  [5] "244077734"  "16900353"   "2404767650" "222061895"
##  [9] "11686382"   "190569306"  "49413866"   "187048879"
## [13] "6146692"    "2591996912"
```

```
## [[1]]
## [1] "bobaiKato: RT @RDataMining: A Twitter dataset for text...
##
## [[2]]
## [1] "VipulMathur: RT @RDataMining: A Twitter dataset for te...
##
## [[3]]
## [1] "tau_phoenix: RT @RDataMining: A Twitter dataset for te...
```

The tweet potentially reached around 120,000 users.


VipulMathur
eliotpbrenner
arnicas
RDataMining
CanberraDataSci
WordLo
PaulineDataWard
mshook
randal_olson
AndrewBaidu
QIMP3G
bobaiKato
tonyquartararo
joshuafoust

Contents

R Packages

- Twitter data extraction: *twitteR*
- Text cleaning and mining: *tm*
- Word cloud: *wordcloud*
- Topic modelling: *topicmodels*, *lda*
- Sentiment analysis: *sentiment140*
- Social network analysis: *igraph*, *sna*
- Visualisation: *wordcloud*, *Rgraphviz*, *ggplot2*

Twitter Data Extraction – Package *twitteR* [§]

- `userTimeline`, `homeTimeline`, `mentions`, `retweetsOfMe`: retrive various timelines
- `getUser`, `lookupUsers`: get information of Twitter user(s)
- `getFollowers`, `getFollowerIDs`: retrieve followers (or their IDs)
- `getFriends`, `getFriendIDs`: return a list of Twitter users (or user IDs) that a user follows
- `retweets`, `retweeters`: return retweets or users who retweeted a tweet
- `searchTwitter`: issue a search of Twitter
- `getCurRateLimitInfo`: retrieve current rate limit information
- `twListToDF`: convert into data.frame

[§] https://cran.r-project.org/package=twitteR

Text Mining – Package *tm* ¶

- `removeNumbers`, `removePunctuation`, `removeWords`, `removeSparseTerms`, `stripWhitespace`: remove numbers, punctuations, words or extra whitespaces
- `removeSparseTerms`: remove sparse terms from a term-document matrix
- `stopwords`: various kinds of stopwords
- `stemDocument`, `stemCompletion`: stem words and complete stems
- `TermDocumentMatrix`, `DocumentTermMatrix`: build a term-document matrix or a document-term matrix
- `termFreq`: generate a term frequency vector
- `findFreqTerms`, `findAssocs`: find frequent terms or associations of terms
- `weightBin`, `weightTf`, `weightTfIdf`, `weightSMART`, `WeightFunction`: various ways to weight a term-document matrix

¶ https://cran.r-project.org/package=tm

Topic Modelling and Sentiment Analysis – Packages *topicmodels & sentiment140*

Package *topicmodels* [‖]

- `LDA`: build a Latent Dirichlet Allocation (LDA) model
- `CTM`: build a Correlated Topic Model (CTM) model
- `terms`: extract the most likely terms for each topic
- `topics`: extract the most likely topics for each document

Package *sentiment140* [**]

- `sentiment`: sentiment analysis with the sentiment140 API, tune to Twitter text analysis

[‖] https://cran.r-project.org/package=topicmodels
[**] https://github.com/okugami79/sentiment140

Social Network Analysis and Visualization – Package *igraph* [††]

- `degree`, `betweenness`, `closeness`, `transitivity`: various centrality scores
- `neighborhood`: neighborhood of graph vertices
- `cliques`, `largest.cliques`, `maximal.cliques`, `clique.number`: find cliques, ie. complete subgraphs
- `clusters`, `no.clusters`: maximal connected components of a graph and the number of them
- `fastgreedy.community`, `spinglass.community`: community detection
- `cohesive.blocks`: calculate cohesive blocks
- `induced.subgraph`: create a subgraph of a graph (*igraph*)
- `read.graph`, `write.graph`: read and writ graphs from and to files of various formats

[††] https://cran.r-project.org/package=igraph

Contents

Wrap Up

- Transform unstructured data into structured data (i.e., term-document matrix), and then apply traditional data mining algorithms like clustering and classification
- Feature extraction: term frequency, TF-IDF and many others
- Text cleaning: lower case, removing numbers, puntuations and URLs, stop words, stemming and stem completion
- Stem completion may not always work as expected.
- Documents in languages other than English

Contents

Further Readings

- Text Mining
  https://en.wikipedia.org/wiki/Text_mining
- TF-IDF
  https://en.wikipedia.org/wiki/Tf\OT1\textendashidf
- Topic Modelling
  https://en.wikipedia.org/wiki/Topic_model
- Sentiment Analysis
  https://en.wikipedia.org/wiki/Sentiment_analysis
- Document Summarization
  https://en.wikipedia.org/wiki/Automatic_summarization
- Natural Language Processing
  https://en.wikipedia.org/wiki/Natural_language_processing
- An introduction to text mining by Ian Witten
  http://www.cs.waikato.ac.nz/%7Eihw/papers/04-IHW-Textmining.pdf

Online Resources

- Chapter 10 – Text Mining, in book *R and Data Mining: Examples and Case Studies*

  `http://www.rdatamining.com/docs/RDataMining-book.pdf`
- RDataMining Reference Card

  `http://www.rdatamining.com/docs/RDataMining-reference-card.pdf`
- Free online courses and documents

  `http://www.rdatamining.com/resources/`
- RDataMining Group on LinkedIn (26,000+ members)

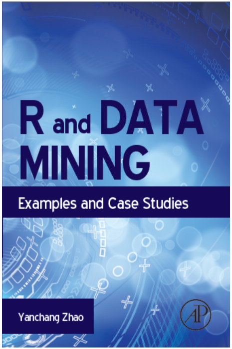
  `http://group.rdatamining.com`
- Twitter (3,300+ followers)

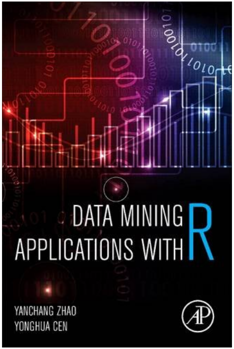
  @RDataMining

References

- Yanchang Zhao. *R and Data Mining: Examples and Case Studies*. ISBN 978-0-12-396963-7, December 2012. Academic Press, Elsevier. 256 pages.
  `http://www.rdatamining.com/docs/RDataMining-book.pdf`
- Yanchang Zhao and Yonghua Cen (Eds.). *Data Mining Applications with R*. ISBN 978-0124115118, December 2013. Academic Press, Elsevier.
- Yanchang Zhao. Analysing Twitter Data with Text Mining and Social Network Analysis. In *Proc. of the 11th Australasian Data Mining & Analytics Conference (AusDM 2013)*, Canberra, Australia, November 13—15, 2013.

The End





Thanks!

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Twitter: `@RDataMining`