Statistical Computing with R Masters in Data Science 503 (S9) Second Batch, SMS, TU, 2023

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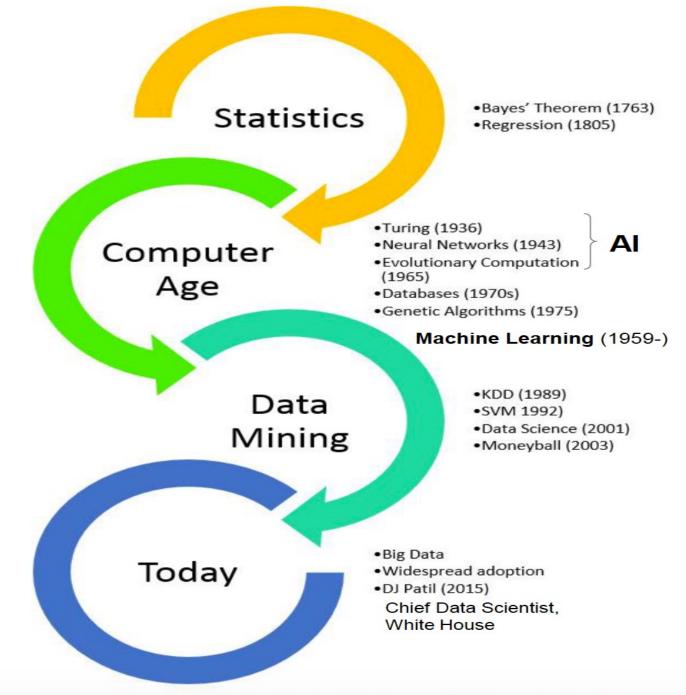
Faculty, FAIMER Fellowship in Health Professions Education, India/USA.

Review Preview (Unit 2, Session 3)

- Data Mining
 - What did you find in this reading provided to you?
 - https://bootcamp.pe.gatech.edu/blog/what-is-data-mining/
- Text Mining
 - What did you find in this reading provided to you?
 - https://rpubs.com/vipero7/introduction-to-text-mining-with-r

Origins of Data Mining

- Draws ideas from AI, machine learning, pattern recognition, statistics, and database systems.
- There are differences in terms of
 - —used data and
 - —the goals.



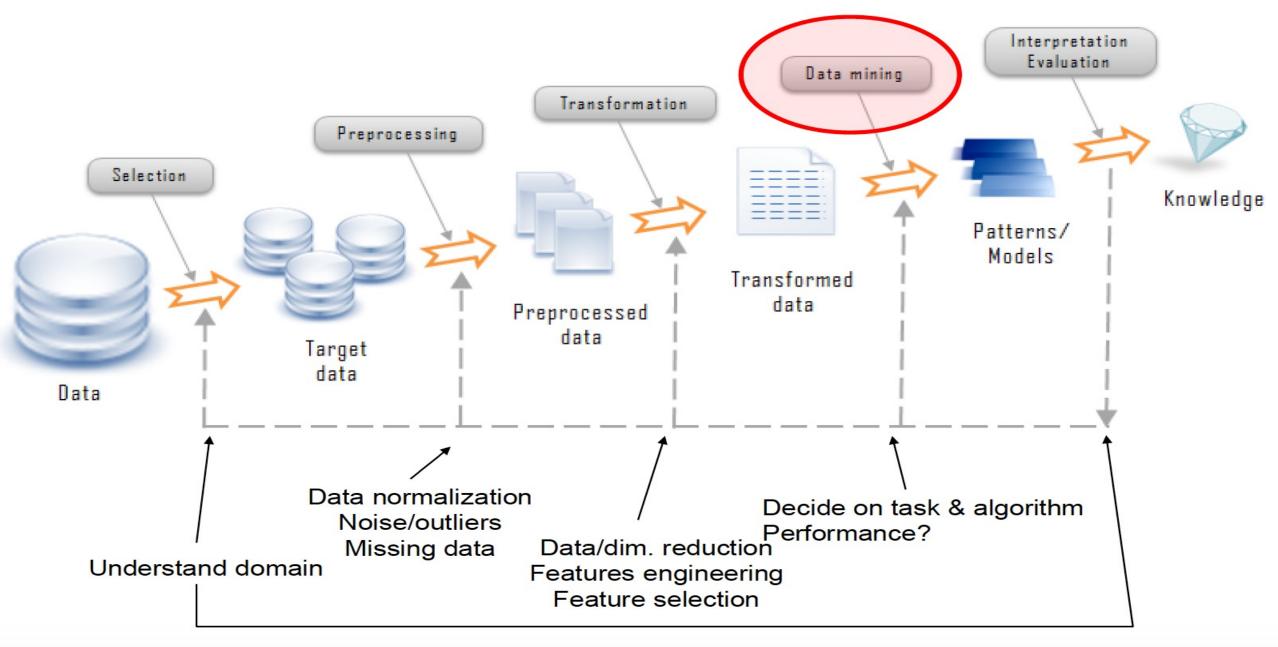
https://rayli.net/blog/data/history-of-data-mining/

Data Mining (What is):

- Data Mining refers to a set of methods applicable to large and complex databases to eliminate the randomness and discover the hidden pattern. (https://online.stat.psu.edu/stat857/node/142/)
- Data Mining is the science of <u>extracting useful information</u> from huge data repositories/warehouse (<u>http://www.kdd.org/curriculum</u>)
- Data Mining helps to:
 - identify patterns and relationships
 - classify and segment data
 - formulate hypothesis

KDD = Knowledge Discovery in/from Database

Knowledge Discovery in Databases (KDD) Process



Usama M. Fayyad, Gregory Piatetsky-Shapiro, and Padhraic Smyth. 1996. From data mining to knowledge discovery: an overview.

Natural Language Data Feature Processing Engineering **Artificial** Graph Science Data Scientific **Analytics Statistics** Intelligence Warehousing Method Mashups **Analytics** Predictive Information Retrieval Simulation Modeling **Databases** Data & Text Machine Learning **Data Management** Mining **Business Intelligence Privacy & Security** Big Data **Programming** scientific mindset curious Computer Data Scientist creative Science business-**Cloud Computing** pragmatic thinking **Distributed Systems** Visualization Technology & Art & Design Infrastructure Communication **Data Product Design Ethics** Entrepreneurship

Domain Knowledge

Source: T. Stadelmann, et al., Applied Data Science in Europe

For Data Science, Data Mining is:

- interdisciplinary and overlaps significantly with many fields such as
 - Statistics
 - Computer Science (Machine Learning, AI, Databases)
 - Optimization
- requires a team effort with members who have expertise in several areas such as
 - Data management
 - Statistics
 - Programming
 - Communication
 - + application domain (health, business, physics, biology etc.)

(IBM) CRISP-DM Reference Model:

• Cross Industry Standard Process for Data Mining (CRISP-DM):

- Business Understanding
- Data understanding
- Data Preparation
- Modelling
- Evaluation
- Deployment

Tasks in the CRISP-DM Model

Business Understanding

Determine Business Objectives Background Business Objectives Business Success Criteria

Assess Situation

Inventory of Resources
Requirements,
Assumptions, and
Constraints
Risks and
Contingencies
Terminology
Costs and Benefits

Data Mining Goals Data Mining Goals Data Mining Success Criteria

Produce Project Plan Project Plan Initial Assessment of Tools and Techniques

Data Understanding

Collect Initial Data Initial Data Collection Report

Describe Data Data Description Report

Explore Data Data Exploration Report

Verify Data Quality Data Quality Report

Data Preparation

Select Data Rationale for Inclusion/ Exclusion

Clean Data Data Cleaning Report

Construct Data Derived Attributes Generated Records

Integrate Data Merged Data

Format Data Reformatted Data

Dataset Dataset Description

Modeling

Select Modeling Techniques Modeling Technique Modeling Assumptions

Generate Test Design Test Design

Build Model Parameter Settings Models Model Descriptions

Assess Model Model Assessment Revised Parameter Settings

Evaluation

Evaluate Results Assessment of Data Mining Results w.r.t. Business Success Criteria Approved Models

Review Process Review of Process

Determine Next Steps List of Possible Actions Decision

Deployment

Plan Deployment Deployment Plan

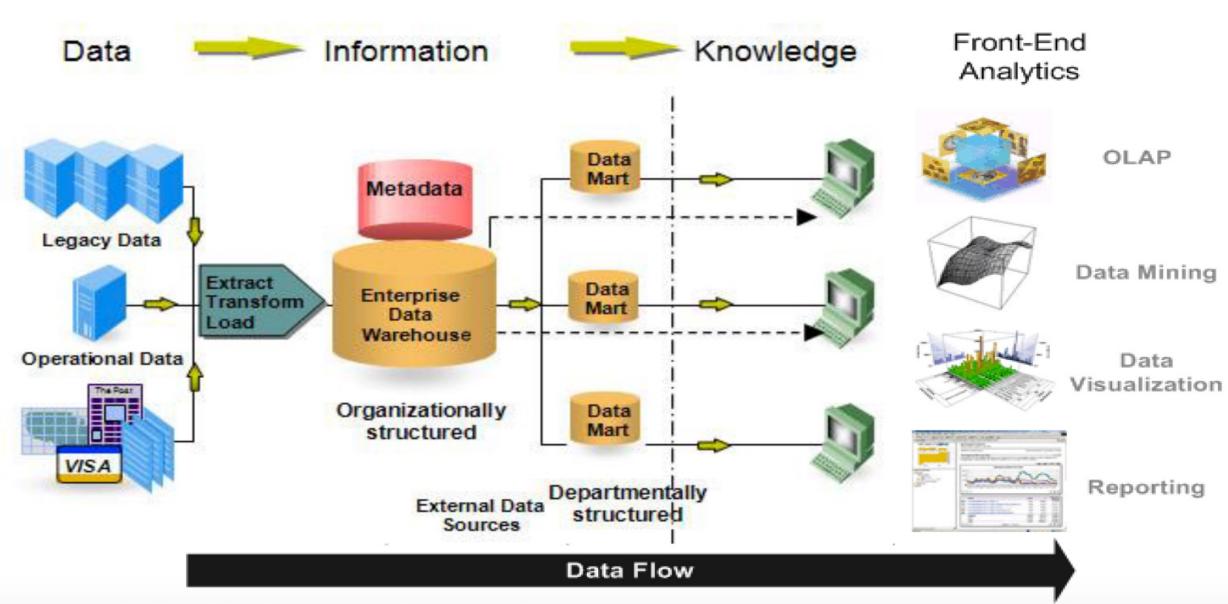
Plan Monitoring and Maintenance Monitoring and Maintenance Plan

Produce Final Report Final Report Final Presentation

Review Project Experience Documentation

Figure 3: Generic tasks (bold) and outputs (italic) of the CRISP-DM reference model

Data Warehouse



What is?

- Data:
 - Legacy data?
 - Operational data?
- ETL process?
- Information:
 - Metadata?
 - Enterprise Data Warehouse?
 - Data Mart?
- Knowledge:
 - OLAP?
 - Data Mining?

• Data:

- Old, obsolete but retained data
- Highly volatile, real time analysis
- Extract, transform, load
- Information:
 - Directory
 - Integrated, static data, analytics
 - Simple form of data warehouse
- Knowledge
 - Online analytical processing
 - Descriptive, predictive, prescriptive

Data Mining Tasks:

- Descriptive Methods:
 - Find human interpretable patterns that describes the data (Unit 1, 2 and 3 of this course)
- Predicting Methods:
 - Use some features (variables) to predict unknown or future value of other variable (Unit 4 and 5 of this course)
- Prescriptive Methods:
 - Optimization
 - Stochastic optimization

Data Mining & Analytics

Stochastic Optimization OR	How can we achieve the best outcome including the effects of variability?	D		
Optimization	How can we achieve the best outcome?	Prescriptive		
Predictive modeling Data Mining / Stats	What will happen next if ?			
Forecasting Statistics	What if these trends continue?	Predictive		
Simulation OR	What could happen?			
Alerts Machine Learning	What actions are needed?			
Query/drill down	What exactly is the problem?			
Ad hoc reporting DB / CS	How many, how often, where?	Descriptive		
Standard Reporting	What happened?			

Degree of Complexity

Data Mining Tasks:

Predictive Modelling (Regression and classification) – Unit 4

Dimensionality Reduction, Cluster Analysis – Unit 5

Association Analysis – Unit 5

Anomaly detection – Not covered in this course

Predictive modelling:

Supervised Learning

- Regression
 - Linear regression (simple and multiple)
 - Logistic regression (bi-variate and multivariate)
- Classification
 - Decision trees, Random forests, Neural networks
 - Support Vector Machines, Naïve Bayes
- We will discuss more on these topics in Unit 4

Dimensionality Reduction: Column/Variable Based Data Reduction Methods

- Unsupervised Learning
- Principal Component Analysis (PCA)
- Principal Axis Factoring (PAF)
- Multidimensional scaling (MDS)
 - Classical (Principal coordinate analysis)
 - Metric MDS, Non-metric MDS
 - Generalized MDS

Cluster Analysis: Row/Case Based Data Reduction Methods (HC, k-means etc.)

Unsupervised Learning

• Data points in one cluster are more similar to one another

Data points in separate clusters are less similar to one another

 We will discuss more on dimension reductions/cluster analysis in Unit 5

Data Mining Tools:

- Simple Graphical User Interface (GUI) based on R
 - Weka
 - Rattle
- Process oriented
 - Rapid Miner
 - IBM SPSS Modeler
 - SAS Enterprise Miner etc.
- Programming oriented
 - R, Rattle, R Studio (shiny), Microsoft R (reticulate package to run python in R)
 - Python, Numpy, Scipy scikit-learn, pandas, Jupyter notebook (rpy2 to run R in python)

Other Data Mining Tasks:

- Text Mining (we will discuss it today with an example from web)
- Graph Mining (Unit 3)
- Data stream mining not covered in this course
- Mining spatiotemporal data (e.g. moving objects) not covered
- Distributed data mining etc. not covered in this course

Question/queries so far?

Text Mining:

- Import texts (Interviews, Twits, Facebook posts, Comments, Reviews etc.) in R
- Transform the texts to data frame and define the "Corpus"
- Perform pre-processing of the "Corpus" using standard methods
- Build document-term matrix (DTM)
- Find frequent terms and associations of key term with other terms
- Use network graph/word cloud to visualize the DTM
- Perform cluster analysis to find clusters of similar words
- Perform "topic modelling" and compare it with network graph result!

Packages required for Text Mining:

• Text mining: *tm*

(Details: https://cran.r-project.org/web/packages/tm/tm.pdf)

• Topic modelling: topicmodels, Ida

Word cloud: wordcloud

Twitter data access: twitteR (Optional)

Example of tweet mining: rdatamining.com

(Alternative solution: https://rstudio-pubs-static.s3.amazonaws.com/66739_c4422a1761bd4ee0b0bb8821d7780e12.html)

Option 1: retrieve tweets from Twitter (must have API keys!)

- library(twitteR)
- tweets <- userTimeline("RDataMining", n = 3200)
- ## Option 2: download @RDataMining tweets from RDataMining.com
- url <- "http://www.rdatamining.com/datasets/rdmTweets.RData" download.file(url, destfile = "./rdmTweets.RData")

Option 3: Download @RDataMining tweeks from RDataMining.com manually: http://www.rdatamining.com/datasets/rdmTweets.RData and save it to the folder you want to use e.g. Downloads!

Load tweets in R, check length and its structure (The "twitteR" package must be installed a priori):

```
load(file = "./rdmTweets.RData")
```

tweets <- rdmTweets

• str(tweets)

#Assign tweets as rdmTweets

```
(n.tweet <- length(tweets))</li>
```

• [1] 154

#If rmdTweets is assigned as "tweets"

#Option 2 used, 154 tweets only!

#Option 2 used!

- strwrap(tweets[[154]]\$text, width = 55) #Text variable of tweet 154
- [1] "An R Reference Card for Data Mining is now available"
- [2] "on CRAN. It lists many useful R functions and packages"
- [3] "for data mining applications."

Checking the content of first three tweets

- tweets[1:3]
- [[1]]
- [1] "RDataMining: Postdoc/Research Scientist Position on Big Data at MIT http://t.co/hZ1ojAW2"
- [[2]]
- [1] "RDataMining: Research scientist position for privacy-preserving data publishing, Singapore http://t.co/GPA0TyG5"
- [[3]]
- [1] "RDataMining: Easier Parallel Computing in R with snowfall and sfCluster http://t.co/BPcinvzK"

Checking the content of the last tweet

#With string wrap and line break at 55th and 62nd positions

- strwrap(tweets[[154]]\$text, width = 55)
- strwrap(tweets[[154]]\$text, width = 62)

#What happens if a single square bracket is used? strwrap(tweets[154]\$text, width = 55)

Output: ?

Why?

Text cleaning in R: Pre-processing I (tweets to data frame and text corpus formation)

- library(twitteR)
- # convert tweets to a data frame
- df <- twListToDF(tweets)
- str(df)

library(tm)

- # build a corpus
- myCorpus <- Corpus(VectorSource(df\$text))
- #Inspect first 3 elements
- inspect(myCorpus[1:3])

Text cleaning in R: Pre-processing I (Corpus to lower case, remove punctuation/numbers)

- # convert to lower case
- myCorpus <- tm_map(myCorpus, tolower)
- inspect(myCorpus[1:3])

- # remove punctuations and numbers
- myCorpus <- tm_map(myCorpus, removePunctuation)
- inspect(myCorpus[1:3])
- myCorpus <- tm_map(myCorpus, removeNumbers)
- inspect(myCorpus[1:3])

Text cleaning in R: Pre-processing II (Remove URL)

remove URLs, http followed by non-space characters

removeURL <- function(x) gsub("http[^[:space:]]*", "", x)

myCorpus <- tm_map(myCorpus, removeURL)

inspect(myCorpus[1:3])

Text cleaning in R: Pre-processing II (Remove Stop Words)

- # remove r and big from the list of stopwords
- myStopwords <- setdiff(stopwords("english"), c("r", "big"))

- # remove stopwords
- myCorpus <- tm_map(myCorpus, removeWords, myStopwords)
- inspect(myCorpus[1:3])

Text cleaning in R: Pre-processing III (Stemming, be careful with this process!)

- # keep a copy of corpus
- myCorpusCopy <- myCorpus
- # stem words
- myCorpus <- tm_map(myCorpus, stemDocument)
- inspect(myCorpus[1:3])
- # stem completion (OPTIONAL:THIS MIGHT NOT WORK!)
- myCorpus <- tm_map(myCorpus, stemCompletion, dictionary = myCorpusCopy)
- inspect(myCorpus[1:3])

We must use
SnowballC package
for proper
stemming if this
does not work!

Text cleaning in R: Pre-processing III (Stemming, be careful with this process!)

replace "posit" with "position", because "position" was first stemmed to "posit" and then completed to "posit"

- myCorpus <- tm_map(myCorpus, gsub, pattern="posit", replacement="position")
- strwrap(myCorpus[154], width=55) #check the corpus again (iteratively)!

- [1] "r reference card data mining now available cran list mani use r"
- [2] "functions packag data mining applic"

Create Term Document Matrix and Check "Frequent terms":

#Create Term Document Matrix and check its structure

- myTdm <- TermDocumentMatrix(myCorpus, control=list(wordLengths=c(1,Inf)))
- str(myTdm)

inspect frequent words

(freq.terms <- findFreqTerms(myTdm, lowfreq=10))

- [1] "data" "posit" "research" "comput" "r" "packag" "tutori"
- [8] "use" "slide" "mine" "analysi" "network" "social" "introduct"
- [15] "exampl" "group"

Check "Associations" with word "r": Association >=0.2 of "r" with other words!

•# which words are associated with r?

```
findAssocs(myTdm, "r", 0.2)
```

```
## r
# mani 0.26 #function 0.24
# canberra 0.26 #use 0.23
# list 0.26
```

What is done here? (This will not work if stemming is not corrected!)

which words are associated with

• findAssocs(myTdm, "position", 0.25)

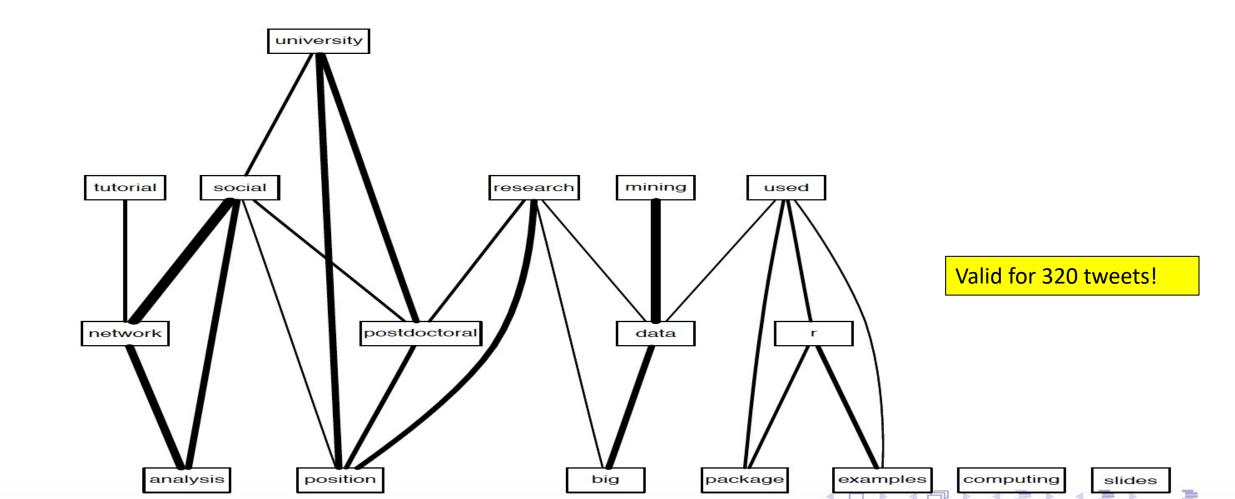
\$position numeric(0)

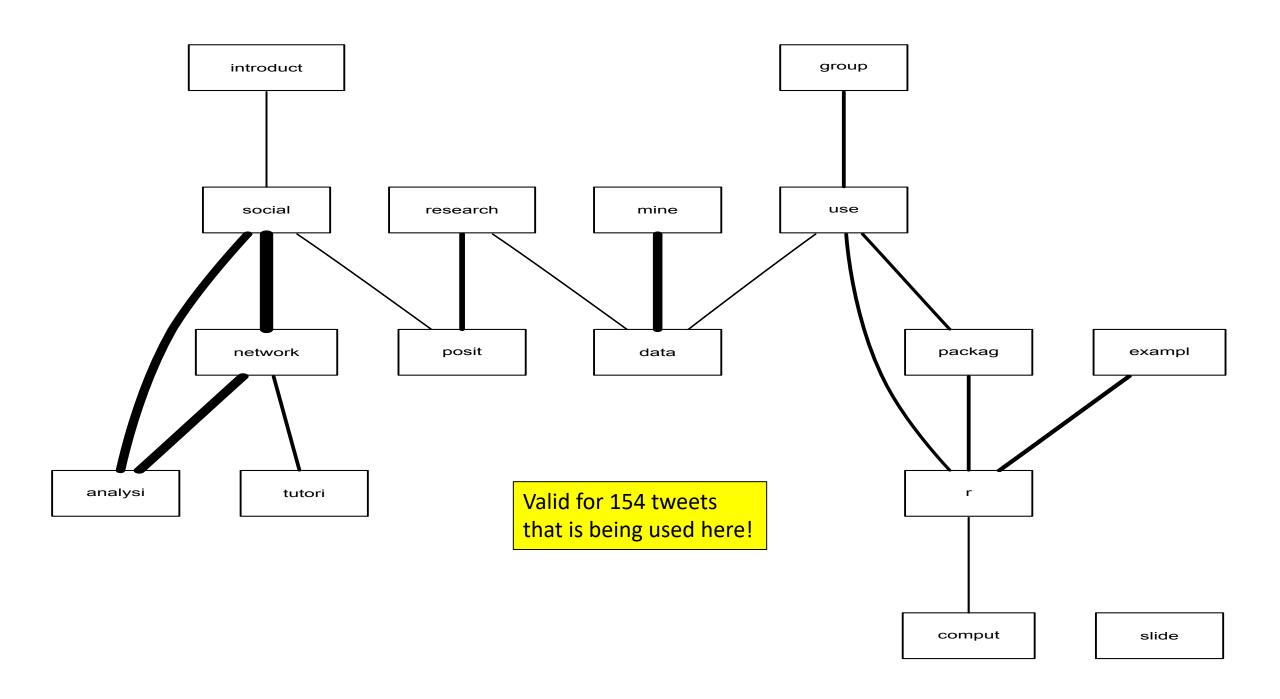
which words are associated with

• findAssocs(myTdm, "posit", 0.25)

Network of Terms

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





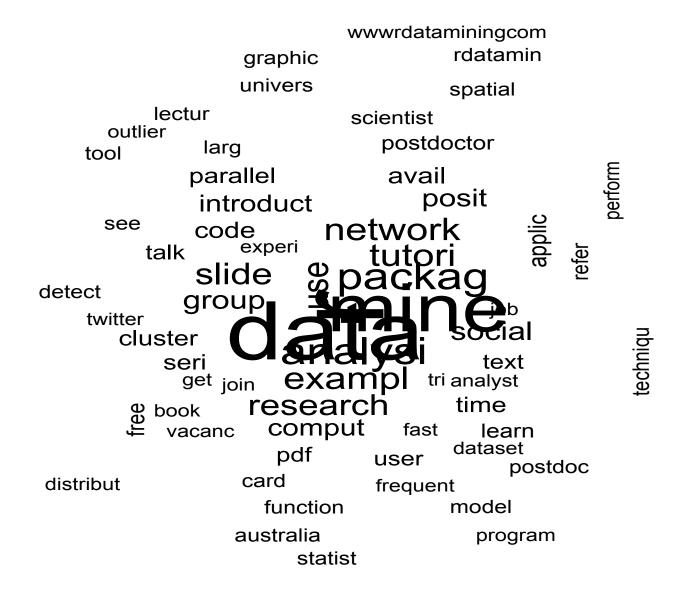
Word cloud:

library(wordcloud)

m <- as.matrix(myTdm)

freq <- sort(rowSums(m), decreasing=T)

 wordcloud(words=names(freq), freq=freq, min.freq=4, random.order=F)



Try it with minimum frequency of 1 and 10

If you want colorful word cloud then use the RColorBrewer package!

More here:

https://www.rbloggers.com/2011/ 07/word-cloud-in-r/

Topic Modelling: "topicmodels" package

library(topicmodels)

• set.seed(123)

• myLda <- LDA(as.DocumentTermMatrix(myTdm), k=5) #5 topics

• terms(myLda, 3) #Three terms in each topic (can be changed)

Note: LDA = Latent Dirichlet Allocation: NLP->ML->AI (Self-learning)

•	Topic 1	Topic 2	Topic 3	Topic 4	Topic 5
• [1,]	"data"	"r"	"analysi"	"r"	"r"
• [2,]	"mine"	"exampl"	"network"	"packag"	"data"
• [3,]	"r"	"code"	"social"	"comput"	"mine"

- Compare this result with the Rgraphviz results obtained above
- Are you happy?
- Do you want to change LDA parameters?
- Change LDA parameters!

Refined model: Four topics with 3 terms each

- set.seed(123)
- > myLda <- LDA(as.DocumentTermMatrix(myTdm), k=4)#5 topics
- > terms(myLda, 3) #Three terms in each topic (can be changed)

•	Topic 1	Topic 2	Topic 3	Topic 4
• [1,]	"data"	"data"	"r"	"r"
• [2,]	"mine"	"research"	"tutori"	"group"
• [3,]	"r"	"r"	"exampl"	"data"

Are you happy with these four topics?

Did it miss something important?

Project 1: Text mining with five pdf files of same content area (journal articles)!

- You must search and download first 5 free pdf files on this topic using Google Scholar (https://scholar.google.com/) (DO NOT USE GOOGLE.COM)
- You must put all the 5 pdf files in a folder called "MDS503P1"
- Use the "pdftools" package to read these five pdf files in R
- Once you read them in R, create a "corpus" and perform text mining
- Submit the R Script file, R markdown file and knitted pdf files for Project 1 work

Question/Queries?

Thank you!

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