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## MANIPAL ACADEMY OF HIGHER EDUCATION

## THIRD TERM POST GRADUATE DIPLOMA IN DATA SCIENCE (FULL TIME) DEGREE EXAMINATION – SEPTEMBER 2018

SUBJECT: DSC 417.1 – UNSTRUCTURED DATA ANALYSIS

Friday, September 28, 2018

Time: 09:30 – 12:30 Hrs. Max. Marks: 100

## **Answer ALL** the questions:

- 1A. While building corpus how to convert all the words to lowercase
  - i) docs = tm\_map(docs, tolower)
  - ii) docs = tm\_map(docs, content\_transformer(tolower))
  - iii) docs = tm map(docs, content transformer(tolower()))
  - iv) docs = tm\_map(docs, content\_transformer(toLower))
- 1B. Which of the following is used to calculate inverse document frequency of a term?
  - i) log(No. of documents in which the term is appearing/No. of documents in the corpus)
  - ii) No. of documents in the corpus/No. of documents in which the term is appearing
  - iii) log(No. of documents in the corpus/No. of documents in which the term is appearing)
  - iv) log(No. of documents in the corups/Frequency of the term in all the documents)
- 1C. Assume the following data. What is the probability P(game | Sports)

Text	Category		
A great game	Sports		
The election was over	Not sports		
Very clean match	Sports		
A clean but forgettable game	Sports		
It was a close election	Not sports		

- i) 2/14
- ii) 4/14
- iii) 2/11
- iv) 2/5

- 1D. Which of the following is true about sparsity?
  - i) Percentage of zeros against total number of values in Document Term Matrix
  - ii) Percentage of non-zeros in Document Term Matrix
  - iii) Percentage of zero with non-zero values in Document Term Matrix
  - iv) None of the above
- 1E. Extracting word cloud in text mining is an example of
  - i) Unsupervised Learning
  - ii) Network Analysis
  - iii) Classification
  - iv) Supervised Learning
- 1F. Which of the following is used to get the terms total frequency in a term document matrix
  - i) Row sums
  - ii) Column sums

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- iii) Column sums divided by total number of documents
- iv) Row sums divided by total number of documents
- 1G. What is the command to restrict the words in a word cloud based on their count of occurrences?
  - i) wordcloud(words\_counts\$words, words\_counts\$Freq, .freq = 50)
  - ii) wordcloud(words\_counts\\$words, words\_counts\\$Freq, min.freq = 50)
  - iii) wordcloud(words\_counts\$words, words\_counts\$Freq, count = 50)
  - iv) wordcloud(words counts\$words, words counts\$Freq, min.count = 50)
- 1H. Which of the following is used for document clustering
  - i) Term Document Matrix
  - ii) Document Term Matrix
  - iii) Bag of words
  - iv) Inverse document frequency
- 1I. In two documents, the word "the" occurs ten times together across both documents. The word "an" occurs in one document but occurs ten times.

Which of the following is well suited for this scenario.

- i) Both have same TFIDF
- ii) TFIDF of the is higher
- iii) TFIDF of an is higher
- iv) Cannot compute TFIDF
- 1J. In LexRank algorithm, the edges between the sentences are based on
  - i) cosine similarity
  - ii) Correlation of words
  - iii) Frequency of words
  - iv) None of the above

 $(2 \text{ marks} \times 10 = 20 \text{ marks})$ 

- 2A. Analyze the challenges in unstructured data analysis?
- 2B. In the following table, the text column contains the tweets from a hashtag #iphone. How does the Term Document Matrix and Document Term Matrix looks for this?

Screenname	Text	Created_at
Sam	Waiting for the new #iphone release	23/06/2017
Madhan	New #iphone technical specifications	22/06/2017
Veera	#iphone 6 prices slashed. Grab yours soon	21/06/2017
Sundeep	Any idea about new #iphone launch date	22/06/2017
	in India? I heard it is on 22/07/2017. Not	
	sure though	

- 2C. Write an R code to compute top 10 most frequent words from a corpus?
- 2D. Explain the need for sentiment analysis? Quote at least two practical applications of it in mobile manufacturing companies?

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- 2E. Write MongoDB shell commands for the following
  - i) Switch to a new database "manipal"
  - ii) Show to all collections in database "manipal"
  - iii) Count all the documents in the collection "tweets"
  - iv) Assume each document in "tweets" collection has a field called words. The value of the field "words" is array of words in that particular tweet. Write a query to filter those documents which has the hashtag "#datascience"
- 2F. How to remove custom and common stop words from corpus. Explain with one example.
- 2G. Explain Vector Representations of Words with an example.
- 2H. Define polarity in sentiment analysis? Explain with one example
- 2I. How can we classify data assets in organizations? Provide at least two example for each type of asset
- 2J. Explain the importance of TF-IDF transformation with an Example.

 $(4 \text{ marks} \times 10 = 40 \text{ marks})$ 

3A. The following table contains the subject of different emails. The category columns denotes whether it is a sports category or not. Using naive baye's algorithm compute the necessary probabilities to classify the new sentence "A very close game", whether it belong to category sports or not? Explain the process and calculations involved in detail.

Text	Category		
A great game	Sports		
The election was over	Not sports		
Very clean match	Sports		
A clean but forgettable game	Sports		
It was a close election	Not sports		

- 3B. A leading multiplex wanted to use social media as reference to decide whether to screen a particular movie or not based on people reaction to the movie's song release, promo, teaser etc.
  - i) Explain the steps involved in scrapping tweets from Twitter API using R for the hashtag "#pari" and storing the same in MongoDB using R. Provide sample R code
  - ii) Explain the steps involved in building sentiment analysis based on polarities along with R code
- 3C. Explain the steps involved in text cleaning along with R Code. Also explain at least 3 challenges involved in text cleaning.
- 3D. Explain the following terms

i) Stemming

ii) TF-IDF

iii) Sentiment polarity

iv) Collections in MongodB

 $(10 \text{ marks} \times 4 = 40 \text{ marks})$ 

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