1. Introduction

Sentimental Analysis on our dataset is implemented both in R programming and SAS Enterprise Miner. Sentimental analysis is nothing but text mining with emotional rating given to the given input data. This is a special type of text mining in which we will extract the subjective information from our data input text, and we will gain knowledge about the emotions, opinions, moods. In other words, the overall sentiments that exist input text.

Our goal of implementing sentiment analysis is to analyse the qualitative info of input text data. There are too many tasks sentiment analysis, so we decided on checks of the polarity of the text which could be positive, negative or neutral. We will also mine emotions in our input text like happy, sad, angry and more.

In R programming, we have packages that help us implement sentimental analysis, syuzhet_vector, bing_vector and afinn_vector which will help us obtain the sentimental qualitative information and its frequency count i.e. number of times those qualitative terms occurred in our input text data.

And in SAS EM, we will use text rule builder node to build a model that classifies reviews into positive, negative and neutral quantitative terms. Text Rule builder node is a boolean rule-based categorizer that automatically generates an ordered set of rules for describing and predicting our target variable.

Finally, we take sentimental analysis results from both R and SAS implementations and try to compile the comparison reports generated individually.

2. Background Research

Sentimental Analysis as we know also called opinion mining is used for analysing and determining emotional in the text whether they are having positive, negative, or neutral vibes. In simple words, this helps us categorize pieces of writing

in qualitive approach. This saves time and effort because sentimental extraction is fully automated algorithm that analyses sentiment of our dataset. This is becoming a popular topic in artificial intelligence, deep learning, machine learning techniques, and natural language processing technologies. Cambria, E., Das, D., Bandyopadhyay, S. and Feraco, A. eds., 2017. A practical guide to sentiment analysis (pp. 1-196). Cham, Switzerland: Springer International Publishing [1].

In other words, opinion mining or sentimental analysis gives us opportunity to explore mindset of reviewers or audience and study the state of text in from opposite point of view. This makes it a great tool for expanded product analytics and market research with precision targeting and scoring of the reviews. Agarwal, Apoorv, Boyi Xie, Ilia Vovsha, Owen Rambow, and Rebecca J. Passonneau. "Sentiment analysis of twitter data." In Proceedings of the workshop on language in social media (LSM 2011), pp. 30-38. 2011 ^[2].

With that in mind, sentimental analysis is applied to our dataset in finding and extracting opinionated data for our text data input. We will also determine polarity (positive or negative), subjective terms and identify opinion holder. Gonçalves, P., Araújo, M., Benevenuto, F. and Cha, M., 2013, October. Comparing and combining sentiment analysis methods. In Proceedings of the first ACM conference on Online social networks (pp. 27-38) [3].

Why do sentimental analysis matter, can be answered how it create perception and understanding of our input text data through the lens. Medhat, W., Hassan, A. and Korashy, H., 2014. Sentiment analysis algorithms and applications: A survey. Ain Shams engineering journal, 5(4), pp.1093-1113 [4]. It is an influential factor in formulating the segmentation of audience of our review data.

Rule-based approach in sentimental analysis implemented on defined description of an opinion to identify. This involves stemming, tokenization, parsing, and lexicon analysis Hutto, C. and Gilbert, E., 2014, May. Vader: A parsimonious rulebased model for sentiment analysis of social media text. In Proceedings of the International AAAI Conference on Web and Social Media (Vol. 8, No. 1) [5]. We are not using lexicon analysis in our research.

SAS EM is a powerful tool with integrated data mining techniques like text parsing, text filtering, text profiling and text segmenting. We will use same in our

research. Jain, V.K. and Kumar, S., 2017. Improving customer experience using sentiment analysis in e-commerce. In Handbook of Research on Intelligent Techniques and Modeling Applications in Marketing Analytics (pp. 216-224). IGI Global ^[6].

3. Exploration of Data Set

We are provided with "hotel_accomodation_reviews.csv" dataset to implement Sentimental Analysis or Opinion mining. We are asked to choose 30 hotel or restaurant as a subset of main dataset to work with. In R we slice and partition data by selecting 30 unique hotel and create a new data subset as shown in Table ¹.

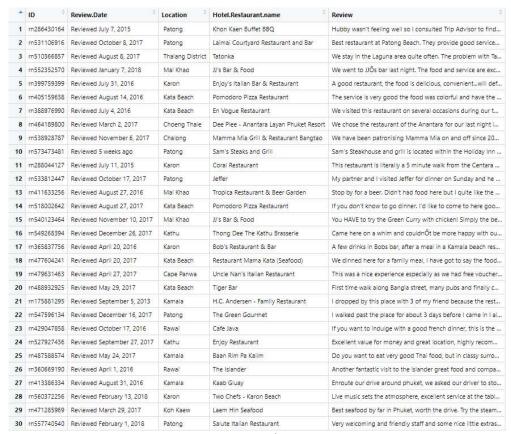


Table ¹

Once our data is ready for implementation, we take one last final look into our data. We'll needing only text field which "review" in our dataset, so we further clean the data by choosing only review column as our data as shown in Table ². We import

our data to respective platform now to implement opinion analysis in R and SAS EM in our next step.



Table ²

4. Sentimental Analysis implementation in R and SAS EM

A. Sentimental Analysis implementation in R

After importing the final dataset acquired after data formatting, we proceed to import it to R studio. We Can also execute data formatting in R as show in output ¹. Here we used sample slicing method to distinguish 30 hotels form the rest and selecting on review column for analysis and save the file to localhost for SAS EM to have same dataset which could be useful in comparison of results purposes as shown in Output ¹.

We start cleansing our data in by transforming our data using corpus function. Removing English stopwords, converting higher cases to lower cases alphabet, removing specific repeated word like "restaurant" and "review", removing punctuations, numbers, spaces, and stemmed words by creating a stem document.

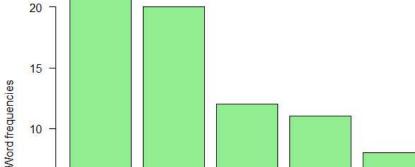
The data then converting into matrix table to identify top frequent word with count as show in Output².

> head	(dtm_d,	5)
		freq
food	food	21
good	good	20
great	great	12
servic	servic	11
amaz	amaz	8
	Output ²	

Plot view of the top 5 most frequent terms is shown in Plot ¹.

5

food



Top 5 most frequent words

servic

good

With the use of wordcloud package, our top frequent terms can be visualized with size factor as shown in Figure ¹.



Figure 1

In our next step we will try find association of top 3 words as show in Output 3 and Output 4 .

```
> findAssocs(reviewed_c_dtm, terms = c("good","food","great"), corlimit = 0.25)
Sgood
numeric(0)

$food
numeric(0)

$great
numeric(0)

Output 3

> findAssocs(reviewed_c_dtm, terms = findFreqTerms(reviewed_c_dtm, lowfreq = 10), corlimit = 0.25)
$food
numeric(0)

$good
numeric(0)

Output 4
```

Unfortunately, we dint find any association for terms "good", "food" and "great". Out frequency output shows the same found no evidence of association.

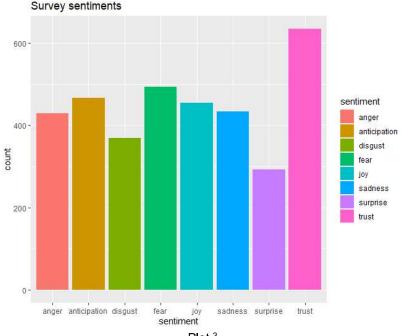
For finding, sentimental qualitative information of our text data, syuzhet_vector, bing_vector and afinn_vector methods are introduced as shown in output ⁵. A matrix comparison vector is created as well.

```
> #regular sentiment score using get_sentiment() function
> # please note that different methods may have different scales
> syuzhet_vector <- get_sentiment(Reviews, method="syuzhet")
> # see the first row of the vector
> head(syuzhet_vector)
[1] 0.00 0.00 0.00 18.35 20.60
> # see summary statistics of the vector
> summary(syuzhet_vector)
   Min. 1st Qu. Median
0.00 0.00 0.00
                              Mean 3rd Qu.
                                               мах.
                             7.79 18.35
> bing_vector <- get_sentiment(Reviews, method="bing")</pre>
> head(bing_vector)
                        9 -319
       0
            0 0
[1]
> summary(bing_vector)
   Min. 1st Qu. Median
                              Mean 3rd Qu.
                                               Max.
                               -62
> afinn_vector <- get_sentiment(Reviews, method="afinn")
> head(afinn_vector)
[1] 0 0 0 29 -94 > summary(afinn_vector)
   Min. 1st Qu. Median
-94 0 0
                            Mean 3rd Qu.
                                               Max.
                              -13
                                          0
                                                 29
> #compare the first row of each vector using sign function
    sign(head(syuzhet_vector)),
    sign(head(bing_vector))
    sign(head(afinn_vector))
     [,1] [,2] [,3] [,4] [,5]
[1,]
         0
                    0
[2,]
        0
              0
                   0
                         1
                             -1
                   0
                         1
                              -1
                               output <sup>5</sup>
```

Setiment nrc gives us scores of our qualitative information from our text data as show in output ⁶.

```
> d<-get_nrc_sentiment(Reviews)
> # head(d,10) - to see top 10 lines of the get_nrc_sentiment dataframe
> head (d,10)
  anger anticipation disgust fear joy sadness surprise trust negative positive
                                0
                   0
                                                                              0
                           0
                                0
                                    0
                                                     0
                                                           0
                                                                    0
                   0
                           1
                                                           0
                                                                              0
                  21
                               10
                                  23
                                                    11
                                                          20
                                                                   11
                                                                             49
    423
                                          430
                         363 482 431
                                                                 1155
                                                                          1197
                 445
                                                         614
                                                   280
                                    output 6
```

We transform the data to visualize the overall sentimental survey results with a bar plot and determine the significance of each emotion from our text input as shown in Plot ³.

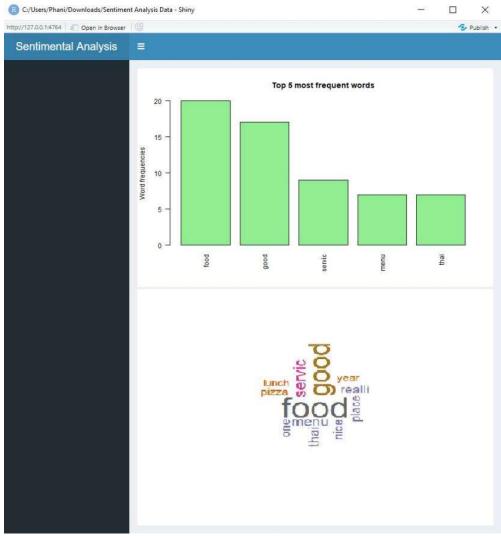


Plot ³

Appendix for Sentimental Analysis

```
| | Load | The ary ("magrittr") # needs to be run every time you start R and want to use %>% | The ary ("magrittr") | Howay ("magrittr") | The ary ("soudhall") | The ary ("soudhall") | The ary ("soudhall") | The ary ("soughall") | The ary ("soughall")
```

Our Shiny Dashboard just display top 5 frequency of terms that are text mined from our data. Picture ¹ shows our results.



Picture 1

Appendix for Shiny Dashboard

```
ui <- dashboardPage(
dashboardHeader(title = "Sentimental Analysis"),
dashboardSidebar(),
dashboardBody(plotOutput("plot1", "plot2" width = 8)))
server <- function(input, output) {
output$plot1 <- renderPlot(barplot(dtm_d[1:5,]$freq, las = 2, names.arg = dtm_d[1:5,]$word,
col = "lightgreen", main = "Top 5 most frequent words",
ylab = "Word frequencies"))
output$plot2 <- renderPlot(quickplot(sentiment, data=td_new2, weight=count, geom="bar", fill=sentiment,
ylab="count")+ggtitle("Survey sentiments"))
}
shinyApp(ui, server)
```

B. Sentimental Analysis implementation on SAS EM

We start by importing the text file saved after sample slicing file in R program from localhost. Figure ² shows our node connection used to achieve opinion mining in SAS EM.

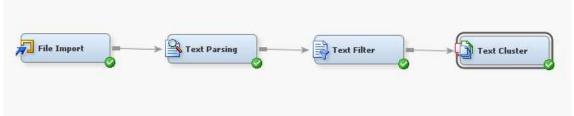
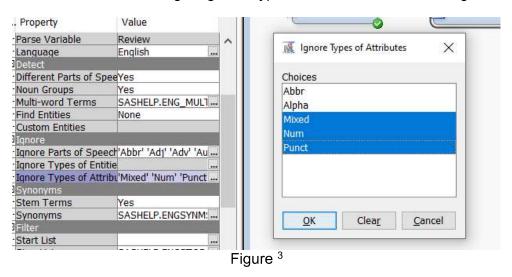
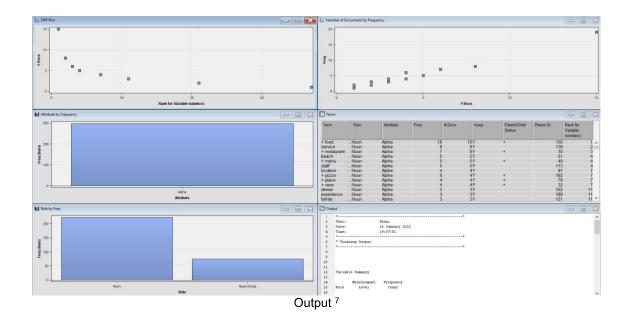


Figure ²

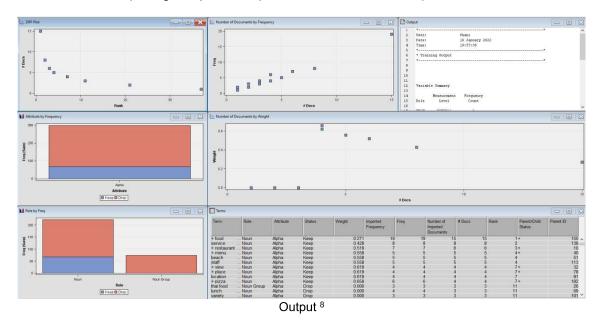
After successful import of the text file, we connect to the Text Parsing node with custom selection of setting to Ignore Type of Attributes as show in Figure ³.



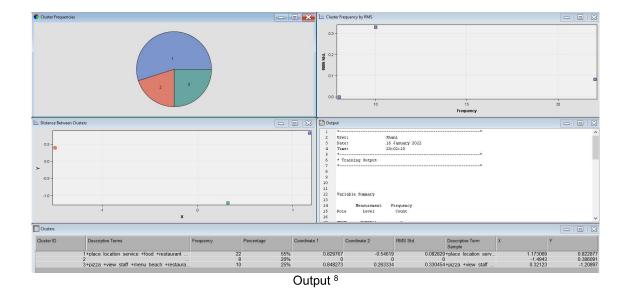
Commencing text parsing yields us following results Output ⁷. We have Rank of Variable numdocs, number of Documents by Frequency, Attribute by Frequency, Terms, Role by Freq, and overall Output. Term count in SAS EM output is evidently higher and proves deeper text mining than that in R.



Connecting to the next node Text Filter gives us the following Output ⁸. In Term results of text filter, we see actual filtering is taking place and status is displayed whether the computing keeps or drops the word from the output.



By connecting Text Filter node to Text Cluster node, we have Output ⁹ computed and this gives Cluster Frequencies with 3 cluster partitions, by RMS as well, and Distance Between Clusters, all 3 Cluster's statistics like coordinates of clusters, RMS standard, location coordinates of clusters on X-Y plane.



5. Conclusions and Comparison of R and SAS EM outputs.

Extracting sentiment from hotel review is successfully implemented in both SAS Enterprise Miner and R studio. Our R programming results are compared with SAS results in this section. When it comes to datamining and extracting sentiment from text R tends towards stricter rule and term creations in producing results and wouldn't be possible without Corpus functions. Plot ³ shows the extracted sentiment measures visually and our review text qualitative results are promising with higher percentage of positive term frequency which conclude, we have higher percentage of positive reviews.

SAS EM creates more terms and term frequency when compared to R. SAS also needs different techniques to be implemented to yield results. Observing all outputs from SAS tells us this has more statistical information than that of R such text clustering and distance of those clusters and co-ordinates on a X-Y plot plane. Descriptive terms are mined in SAS which is a pointer that SAS is notch higher in producing results. By now, we can easily draw a conclusion that SAS text mining is evidently superior in producing accurate and segmented output, But R can be used for a very strict mining and just mining sentiment from the text.

References

- 1. Cambria, E., Das, D., Bandyopadhyay, S. and Feraco, A. eds., 2017. A practical guide to sentiment analysis (pp. 1-196). Cham, Switzerland: Springer International Publishing.
- Agarwal, Apoorv, Boyi Xie, Ilia Vovsha, Owen Rambow, and Rebecca J. Passonneau. "Sentiment analysis of twitter data." In Proceedings of the workshop on language in social media (LSM 2011), pp. 30-38. 2011.
- 3. Gonçalves, P., Araújo, M., Benevenuto, F. and Cha, M., 2013, October. Comparing and combining sentiment analysis methods. In Proceedings of the first ACM conference on Online social networks (pp. 27-38).
- 4. Medhat, W., Hassan, A. and Korashy, H., 2014. Sentiment analysis algorithms and applications: A survey. Ain Shams engineering journal, 5(4), pp.1093-1113.
- Hutto, C. and Gilbert, E., 2014, May. Vader: A parsimonious rule-based model for sentiment analysis of social media text. In Proceedings of the International AAAI Conference on Web and Social Media (Vol. 8, No. 1).
- Jain, V.K. and Kumar, S., 2017. Improving customer experience using sentiment analysis in e-commerce. In Handbook of Research on Intelligent Techniques and Modeling Applications in Marketing Analytics (pp. 216-224). IGI Global.