Algorithm Aversion

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Contents

Motivation: Erwin	1
Data retrieval $\&$	1
Data processing: Mathias	1
Analysis	3
Progression over the years	4
Distribution of classes by topic	5
Conclusion:	6
Critique: Alina	6
Github Repository	6
R Markdown	6
Including Plots	6
Header 1	6
Header 2	6

Motivation: Erwin

Data retrieval &

Data processing: Mathias

```
library(tidyverse)
library(tidytext)
library(textdata)
library(dplyr)
library(vader)
library(academictwitteR)
library(data.table)
library(readr)
library(boot)
used libraries
## 'summarise()' has grouped output by 'alg.data$Year'. You can override using the '.groups' argument.
## 'summarise()' has grouped output by 'Year'. You can override using the '.groups' argument.
listofdfs <- list()</pre>
#data group for cummulated dataframe
for (i in c(7:13)){
  alg.data %>%
   filter(alg.data[,i]>=1)%>%
   mutate(Topic = colnames(alg.data)[i], VADERclass=as.factor(VADERclass))%>%
   group_by(Year,Topic,VADERclass, .drop=FALSE)%>%
    summarise(Sent = n(), .groups = "drop") ->listofdfs[[i]]
}
summ.cumm <- bind_rows(listofdfs)</pre>
#adds percentage to cummulated DF
summ.cumm <-
 summ.cumm %>%
  group by (Topic, Year) %>%
 mutate(All = sum(Sent), percent=(100*Sent/All))
summ.cumm
## # A tibble: 324 x 6
## # Groups: Topic, Year [84]
##
      Year Topic
                    VADERclass Sent
                                        All percent
##
                                <int> <int>
      <dbl> <chr>
                     <fct>
                                              <dbl>
## 1 2010 Business Aversive
                                   2
                                        297
                                              0.673
## 2 2010 Business Negative
                                  14
                                        297
                                              4.71
## 3 2010 Business Neutral
                                  226
                                        297 76.1
## 4 2010 Business Positive
                                  55
                                        297 18.5
## 5 2011 Business Aversive
                                   7
                                        337
                                              2.08
## 6 2011 Business Negative
                                  17
                                        337
                                              5.04
## 7 2011 Business Neutral
                                        337 64.4
                                  217
## 8 2011 Business Positive
                                   96
                                        337 28.5
## 9 2012 Business Aversive
                                  4
                                        357
                                              1.12
## 10 2012 Business Negative
                                   36
                                        357 10.1
## # ... with 314 more rows
```

```
#data group for topic oriented dataframe
listofdfs <- list()</pre>
for (i in c(7:13)){
  alg.data %>%
   filter(alg.data[,i]>=1)%>%
   mutate(Topic = colnames(alg.data)[i])%>%
   group_by( VADERclass, Topic) %>%
   summarise(Sent = n()) ->listofdfs[[i]]
}
summ.topic <- bind_rows(listofdfs)</pre>
#adds percentage to topicwise DF
summ.topic<-</pre>
 summ.topic %>%
  group_by(Topic) %>%
 mutate(All = sum(Sent), percent=(100*Sent/All))
head(summ.topic)
## # A tibble: 6 x 5
## # Groups: Topic [2]
## VADERclass Topic
                           Sent All percent
    <chr> <chr> <chr> <chr> <int> <int> <int> <dbl>
## 1 Aversive Business
                             73 3928 1.86
                          73 3928
373 3928
## 2 Negative Business
                                        9.50
                           2165 3928 55.1
## 3 Neutral Business
## 4 Positive Business 1317 3928 33.5
## 5 Aversive Social.Media 1601 43621
                                         3.67
## 6 Negative Social.Media 5918 43621 13.6
#-----Test wordgroups-----
listofdfs <- list()</pre>
for (i in c(7:13)){
 alg.data %>%
   filter(alg.data[,i]>=1)%>%
   mutate(Topic = colnames(alg.data)[i])%>%
    sample_n(size = 20)%>%
  group_by( VADERclass, Topic) ->listofdfs[[i]]
```

Analysis

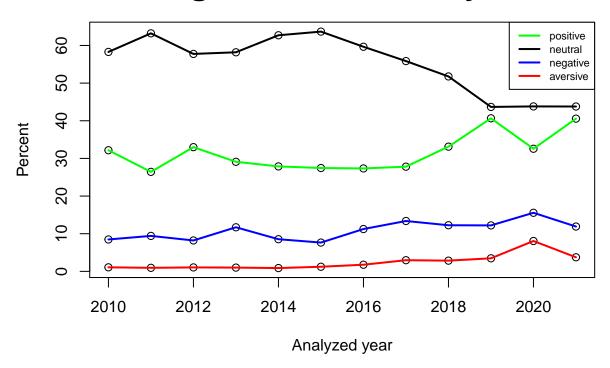
Wordgrouptest<- bind_rows(listofdfs)</pre>

a

Progression over the years

The diagram shows the percentage progression of the results of the sentiment analysis of tweets over the years 2010 to 2021. Values between 0.3 and -0.3 were classified as neutral. As positive between 0.3 and 1, as negative between -0.3 and -0.7 and finally as aversive values between -0.7 and -1. A total of 143271 tweets were analyzed. The fewest tweets were aversive and most were neutral since all tweets not evaluated in the sentiment analysis are classified as neutral.

Progression over the years



Over time, the number of neutral tweets decreases. In 2010, there were 6934 tweets and 58.3%. In 2015, the most neutral tweets were posted with an absolute of 7641 tweets and 63.8% posted. In 2019 the fewest mi 5241 and 43.7% were posted. 2021 total 5254 which is 43.8%. The last 3 years the number of neutral tweets remained at the same level.

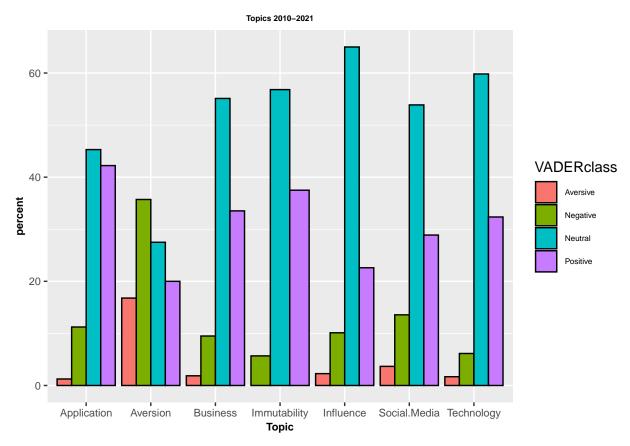
An increasing trend can be seen in the number of positive tweets. In 2010, there were 3827 tweets and 32.2%. In 2019, the most positive tweets were posted with absolute 4878 tweets and 40.7% posted. In 2011 the least mi 3171 and 26.7% were posted. 2021 total 4868 which is 40.6%. The last 3 years the number of positive tweets remained high, with a bump in 2020 with 3908 and 32.6%.

Negative tweets show an increasing trend. In 2010, there were 1008 tweets and 8.5%. In 2020 the most positive tweets were posted with absolute 1867 tweets and 15.6% posted. In 2015 the least mi 918 and 7.7% were posted. In 2021 a total of 1429 which gives 11.9%.

The aversive tweets behave similarly to the negative tweets $2011\ 113\ 0.95\%$ there were the fewest were $2014\ 105$ and 0.88% with the most there were $2020\ 968\ 8.1\%$ and 2021 there were 3.7% and 449 tweets.

Distribution of classes by topic

This graph shows the different topics, Business, Social Media, Technology, Immutability, Influence, Application and Aversion as well as the percentage distribution cer VADER classes Aversive Negative Neutral and Positive.



The topic Aversion has the most aversive tweets with 16.8% and 35% negative tweets, so there are more negative tweets in this topic than positive 20%. The least in Application here there are no negative tweets at all.

Conclusion:

Critique: Alina

Github Repository

https://github.com/sonnleit/AlgorithmAversion

R Markdown

This is an R Markdown document. Markdown is a simple formatting syntax for authoring HTML, PDF, and MS Word documents. For more details on using R Markdown see http://rmarkdown.rstudio.com.

When you click the **Knit** button a document will be generated that includes both content as well as the output of any embedded R code chunks within the document. You can embed an R code chunk like this:

#summary(cars)

Including Plots

You can also embed plots, for example:

Note that the echo = FALSE parameter was added to the code chunk to prevent printing of the R code that generated the plot.

Header 1

Header 2

Header 3

Header 4

Header 5 Header 6