



Caption Analysis Capstone Project

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Project Background

- Dominance of social media in this digital age; Interested in the power of captions on popular social media platforms
- Help our client explore what features of a caption could increase interaction and engagement on social media posts
- Chose to focus on three major social media platforms: **LinkedIn, Twitter and Facebook;** Found accounts similar to the profile of our client: small-scale, non-profit companies
- Discarded the previous dataset and collected our own data using web scraping

Research Questions

As for companies similar to PSI, with the control of number of followers, what factors of caption would have the strongest association with the engagement of their social media posts on Facebook, Twitter and Linkedin?





DATA











- Python
- Scraped data with GitHub open source packages
- Post from accounts that PSI designated
- Up-to-date till Oct 19, 2022
- Initial information collected:
 - Name of the company
 - Text of the caption
 - Likes
 - Comments
 - **Followers**



in LinkedIn

149 observations from **5** Companies



Twitter

105 observations from **8** Companies



Facebook

150 observations from **2** Companies



Data Cleaning

Special Characters

- Count the number of emojis, hashtags, and question marks in each post
- Packages used (Python): advertools, re

Word Count and Length

- Transform text into corpus
- Remove common stop words and special characters
- Calculate the number of words and average length of words in each post
- Packages used (Python): nltk, re

Sentiment

- Compute sentiment for each post
- Packages used (R): SentimentAnalysis





Variables of Interest

SentimentGI	The sentiment of the post text; Quantitative; Ranging from -1 to 1
Hashtag	The number of hashtags included in the post; Quantitative
Question mark	The number of question marks included in the post; Quantitative
Emoji	The number of emojis included in the post; Quantitative
Average length	The average length (number of letters) of the words in the post; Quantitative
Word count	The number of words in the post; Quantitative
С	The number of followers that the account has; Control variable, not of interest

Response	The responses that a post receives; Comments + Likes; Quantitative
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SentimentGI	The sentiment of the post text; Quantitative; Ranging from -1 to 1
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Emoji	The number of emojis included in the post; Quantitative
Average length	The average length (number of letters) of the words in the post; Quantitative
Word count	The number of words in the post; Quantitative
Followers*	The number of followers that the account has; Control variable, not of interest

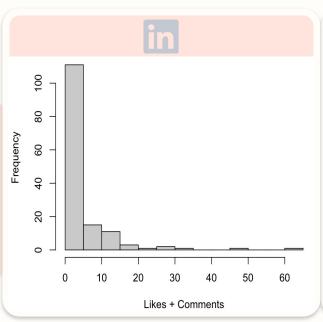
The responses that a post receives; Comments + Likes; Quantitative

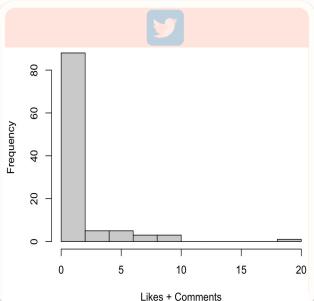
Response

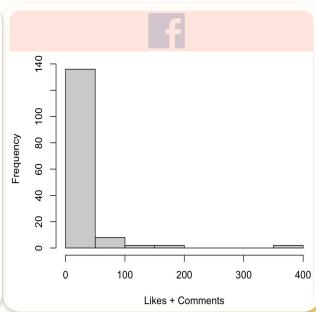


Response Variable Transformation

- Plotted histograms of response variable across all three platforms
- Highly right-skewed distribution, nearly 90% low values (includes 0)
- Need to perform log transformation



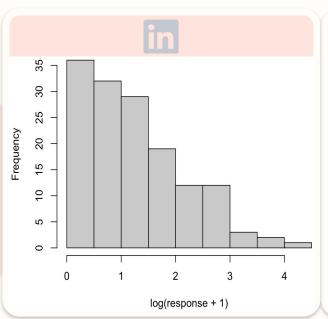


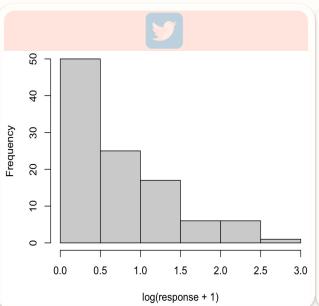


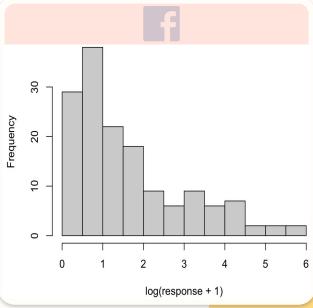


After Log Transformation

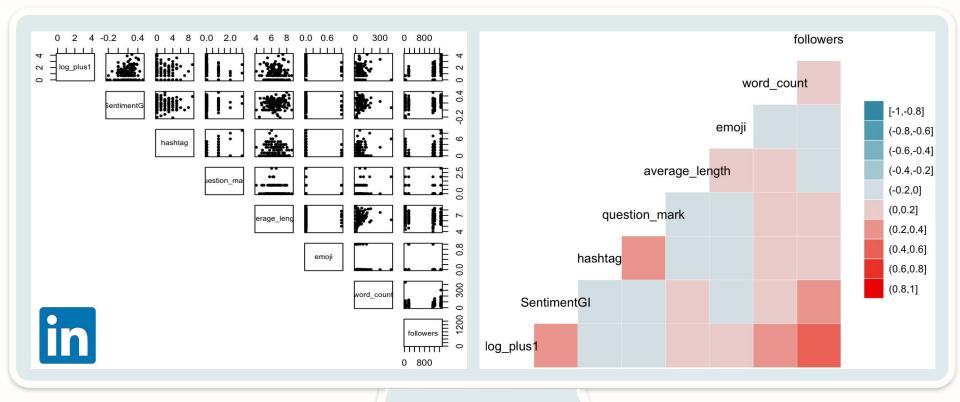
- Applied log(y+1) on all response variables
- $\log(0)$ = undefined \rightarrow error, $\log(1)$ = 0
- Impossible normal distribution, no longer heavily skewed



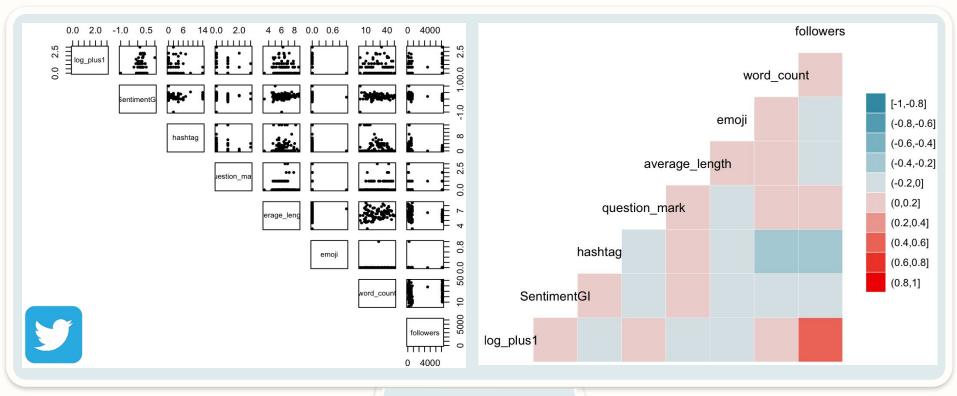




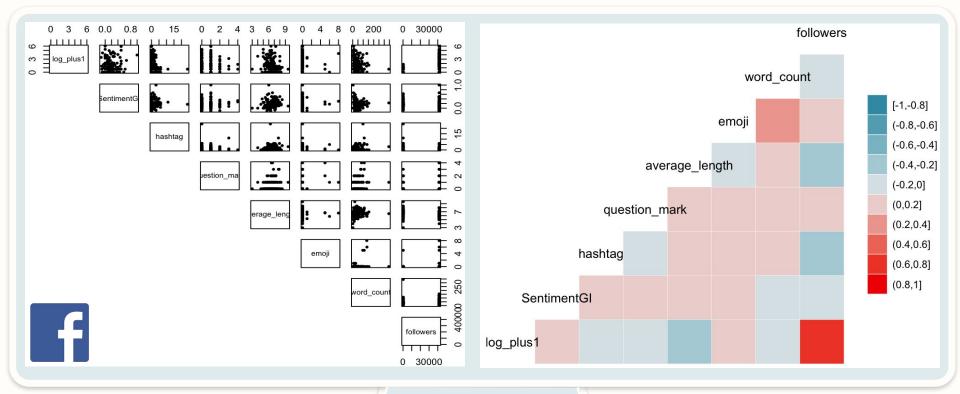
Exploratory Data Analysis



Exploratory Data Analysis



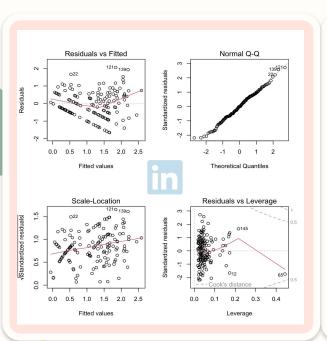
Exploratory Data Analysis

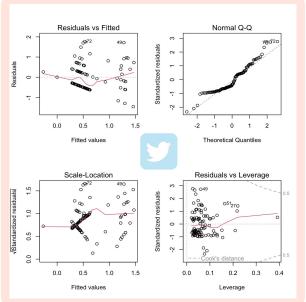


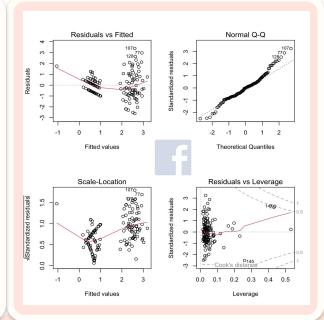
Linear Regression - Assumptions check

The errors, for each fixed value of x,

- 1) have mean 0
- 2) have constant variance
- 3) are independent
- 4) follow a normal distribution.







LinkedIn



Model Building



Linear Regression - LinkedIn

Significant Predictors

SentimentGI (p = .0343)

Question_mark (p = .040)

Emoji (p = .002)

Word_count (p = .024)

Followers* (p < .001)

Adjusted R-squared

0.3998

F-statistic

F(138) = 14.8 (p < .001)

```
Residuals:
    Min
              10
                  Median
-1.65726 -0.51372 0.00378 0.53597 2.05347
Coefficients:
                Estimate Std. Error t value Pr(>|t|)
(Intercept)
              0.3338731 0.4783368
                                    0.698 0.48636
SentimentGI
              1.0437475 0.4881051
                                    2.138 0.03425 *
hashtaa
              -0.0072577 0.0344716 -0.211 0.83356
question_mark -0.2247075 0.1084438 -2.072 0.04012 *
average_length -0.0293008 0.0719516 -0.407 0.68447
                                    3.190 0.00176 **
emoji
              0.9098001 0.2852374
followers 0.0009567 0.0001154
                                    8.293 8.84e-14 ***
word_count
              0.0028220 0.0012367
                                    2.282 0.02402 *
Signif. codes: 0 '*** 0.001 '** 0.01 '* 0.05 '.' 0.1 ' ' 1
Residual standard error: 0.7667 on 138 degrees of freedom
  (3 observations deleted due to missingness)
Multiple R-squared: 0.4288, Adjusted R-squared: 0.3998
F-statistic: 14.8 on 7 and 138 DF, p-value: 2.638e-14
```

Improved Linear Regression - LinkedIn

Likelihood Ratio Test

p = 0.897

Significant Predictors

SentimentGI (p = .032)

Question_mark (p = .030)

Emoji (p = .002)

Word_count (p = .026)

Followers* (p < .001)

Adjusted R-squared

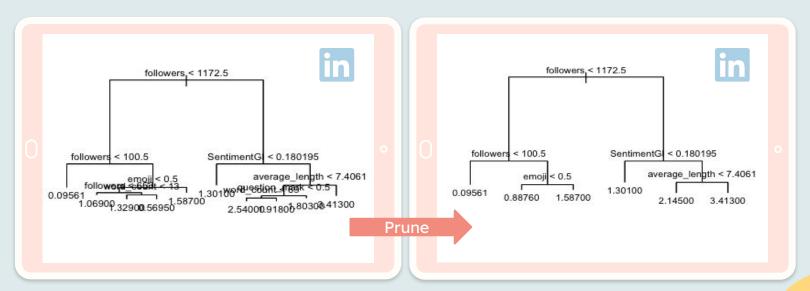
0.4075 (originally 0.3998)

```
Residuals:
   Min
            10 Median
-1.6302 -0.5241 -0.0087 0.5201 2.0494
Coefficients:
               Estimate Std. Error t value Pr(>|t|)
(Intercept)
             0.1393971 0.1423708
                                   0.979 0.32921
SentimentGI
             1.0311503 0.4754367 2.169 0.03178 *
question_mark -0.2270002 0.1038036 -2.187 0.03042 *
emoji
             0.9101241 0.2816855 3.231 0.00154 **
word count
            0.0027064 0.0012012 2.253 0.02580 *
             0.0009591 0.0001136 8.443 3.52e-14 ***
followers
Signif. codes: 0 '*** 0.001 '** 0.01 '* 0.05 '.' 0.1 ' '1
Residual standard error: 0.7618 on 140 degrees of freedom
  (3 observations deleted due to missingness)
Multiple R-squared: 0.428, Adjusted R-squared: 0.4075
F-statistic: 20.95 on 5 and 140 DF, p-value: 1.362e-15
```



Regression Tree - LinkedIn

- Important predictors: **Sentiment, Emoji Counts, Average Length,** Followers*
- Pruning: **6 terminal nodes** selected from 10-fold Cross Validation
- Interpretation example:
 - For accounts with more than **1173 followers**, post with **slightly positive sentiment** (greater than 0.18) and average word length greater than **7 letters** are predicted to receive **3 to 4** likes and comments.





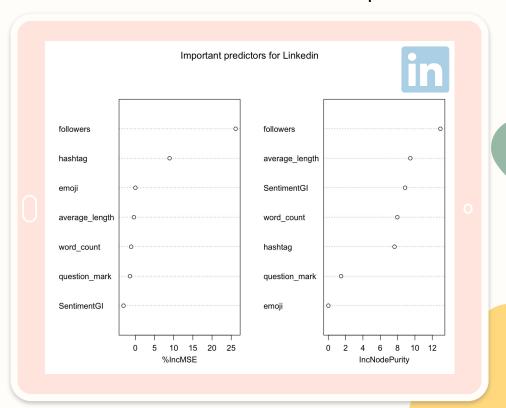
Number of trees: 500

No. of variables tried at each split: 4

Mean of squared residuals: 0.50

% Var explained: 4.55

	%IncMSE	IncNode Purity
SentimentGI	-3.10	8.87
hashtag	8.93	7.65
question_mark	-1.40	1.48
average_length	-0.40	9.47
emoji	0	0.01
followers	26.16	12.94
word_count	-1.11	7.97



Twitter



Model Building



Linear Regression - Twitter

Significant Predictors

SentimentGI (p = .061) Followers* (p < .001)

Adjusted R-squared

0.1943

F-statistic

F(97) = 4.584 (p < .001)



Min 1Q Median 3Q Max -1.4585 -0.4509 -0.2127 0.3136 1.7716



Coefficients:

```
Estimate Std. Error t value Pr(>|t|)
(Intercept)
              5.602e-01 4.287e-01 1.307
                                        0.1944
SentimentGT
              5.965e-01 3.141e-01 1.899 0.0605 .
hashtaa
             -4.646e-03 1.843e-02 -0.252
                                        0.8015
question_mark 1.673e-03 1.039e-01 0.016
                                        0.9872
average_length -4.118e-02 6.621e-02 -0.622 0.5354
emoji
            -3.663e-01 6.601e-01 -0.555
                                         0.5802
followers 1.499e-04 2.996e-05 5.002 2.52e-06 ***
word count
             -3.848e-04 5.288e-03 -0.073
```

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' '1

Residual standard error: 0.6498 on 97 degrees of freedom Multiple R-squared: 0.2486, Adjusted R-squared: 0.1943 F-statistic: 4.584 on 7 and 97 DF, p-value: 0.0001852

Linear Regression - Twitter

Likelihood Ratio Test

p = 0.9953

Significant Predictors

SentimentGI (p = .057) Followers* (p < .001)

Adjusted R-squared

0.218 (originally 0.1943)

Residuals: Min

Min 1Q Median 3Q Max -1.4595 -0.4692 -0.2118 0.3192 1.7613



Coefficients:

```
Estimate Std. Error t value Pr(>|t|)

(Intercept) 5.406e-01 4.135e-01 1.307 0.1940

SentimentGI 5.959e-01 3.089e-01 1.929 0.0566 .

average_length -4.162e-02 6.393e-02 -0.651 0.5165

emoji -3.546e-01 6.479e-01 -0.547 0.5854

followers 1.515e-04 2.807e-05 5.397 4.57e-07 ***

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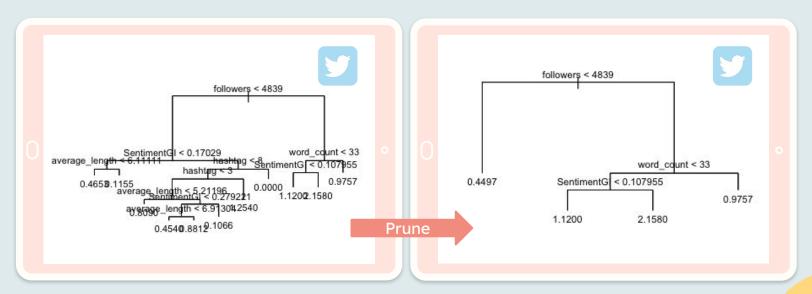
Signif. codes: 0 '***' 0.001 '**' 0.05 '.' 0.1 ' ' 1
```

Residual standard error: 0.6402 on 100 degrees of freedom Multiple R-squared: 0.2481, Adjusted R-squared: 0.218 F-statistic: 8.247 on 4 and 100 DF, p-value: 8.636e-06



Regression Tree - Twitter

- Important predictors: Word Counts, Sentiments, Followers*
- Pruning: **4 terminal nodes** selected from 10-fold Cross Validation
- Interpretation example:
 - For accounts with more than **4839 followers**, post with less than **33 words** and a **slightly positive sentiment** (greater than 0.1) are predicted to receive **2** likes and comments.





Random Forest - Twitter

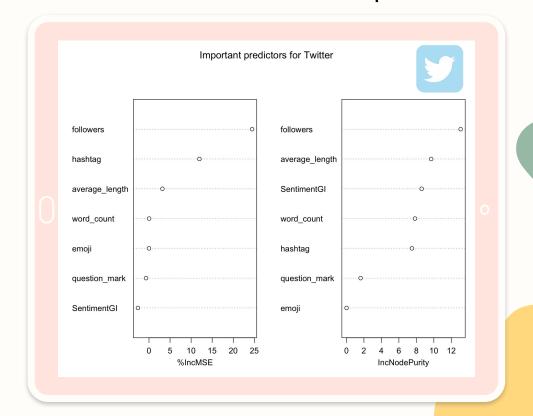
Number of trees: 500

No. of variables tried at each split: 4

Mean of squared residuals: 0.48

% Var explained: 7.16

	%IncMSE	IncNode Purity
SentimentGI	-2.62	8.61
hashtag	11.97	7.49
question_mark	-0.70	1.62
average_length	3.19	9.69
emoji	0	0.02
followers	24.47	13.06
word_count	0.04	7.84



FaceBook



Model Building



Improved Linear Regression - FaceBook

Significant Predictors

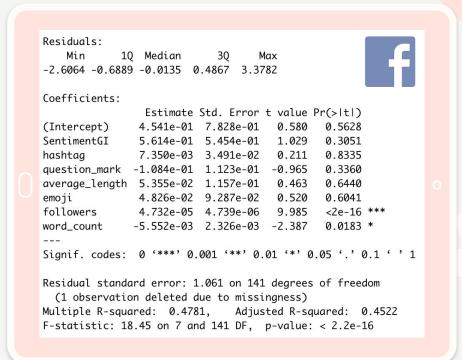
Followers* (p < .001) Word_count (p = .018)

Adjusted R-squared

0.4522

F-statistic

F(141) = 18.45 (p < .001)



Improved Linear Regression - FaceBook

Likelihood Ratio Test

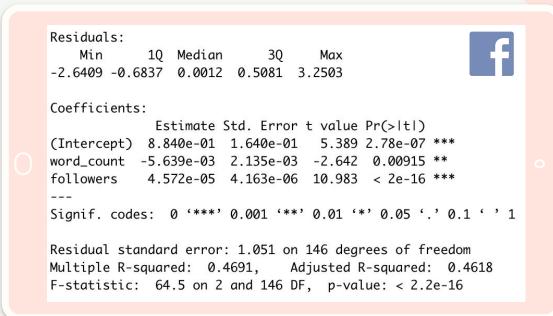
p = .768

Significant Predictors

Followers* (p < .001) Word_count (p = .009)

Adjusted R-squared

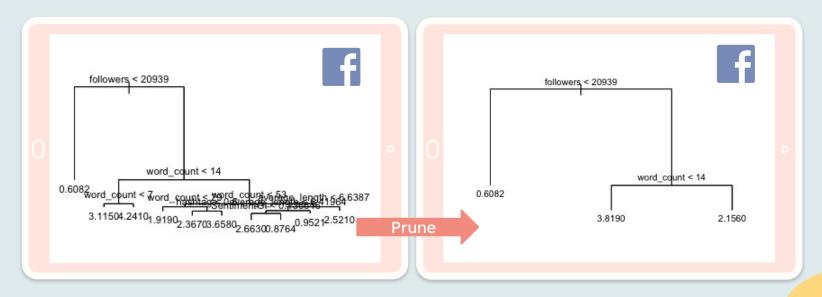
0.4618 (originally 0.4522)





Regression Tree - FaceBook

- Important predictor: Word Counts, Followers*
- Pruning: **3 terminal nodes** selected from 10-fold Cross Validation
- Interpretation example:
 - For accounts with more than **20939 followers**, post with less than **14 words** are predicted to receive **3.8** likes and comments.





Random Forest - FaceBook

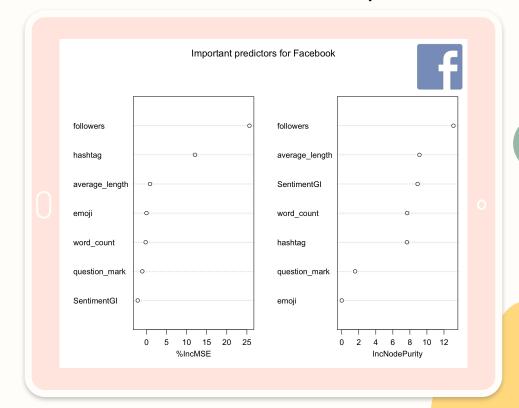
Number of trees: 500

No. of variables tried at each split: 4

Mean of squared residuals: 0.49

% Var explained: 6.14

	%IncMSE	IncNode Purity
SentimentGI	-2.18	8.91
hashtag	12.07	7.65
question_mark	-1.04	1.57
average_length	0.89	9.12
emoji	0	0.01
followers	25.63	13.11
word_count	-0.21	7.68





Conclusion







Conclusion & Recommendation

in LinkedIn

- **Sentiment, Emoji, Average_Length** are the most important predictors
- Choose a more positive tone, use more hashtags and longer words

Twitter

- **Sentiment** is the most important predictor
- Choose a more positive tone

FaceBook

- **Word_count** is the most important predictor
- Be concise and avoid tedious long sentences



Limitation - Data

01

Unbalanced Data

- Due to limitation of the open-source packages, some accounts cannot be scrapped
- A limit to the number of posts that can be scrapped from each platform
 - Log in requirement
 - Scraping restriction that results in disabling the package
- Small company size leads to few followers and low responses

02

Transformed response variable to log(y+1)

- Highly right-skewed response variable
- Presence of 0 in response variable of some observations
- Unable to simply apply log transformation
- Unusual but valid transformation



Limitation - Model Building

- O1 Small sample size: 100-150 posts for every platform
 - Unable to split training data and test data
 - Less powerful models
 - High variance
 - **702** Future Improvement
 - Collect more data
 - Consider using Ridge Regression to reduce variance when sample size is small



Reference

Packages:

- https://github.com/shaikhsajid1111/twitter-scraper-selenium
- https://github.com/kevinzg/facebook-scraper
- https://github.com/daniyalrmb/LinkedIn-Scraping-Sentiment
- https://advertools.readthedocs.io/en/master/
- https://www.nltk.org/howto.html
- https://cran.r-project.org/web/packages/SentimentAnalysis/SentimentAnalysis.pdf



Thank you for listening!



