A Sentiment Analysis of COVID-19 Tweets and its effects on Likeability and Retweet-ability

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Presentation Overview

- 1. Research
- 2. Overview
- 3. Pre-Python
- 4. Import
- 5. Cleaning
- 6. New Feature
- 7. Basic Analysis
- 8. Linear Regression
- 9. Polynomial Regression
- 10. Comparison
- 11. Conclusion



Research Problem

To study whether a tweet's sentimentality and other features have an influence on the tweet's retweet-count and liked-counts.

Key Objectives

- Reduce noise in our dataset
- Create new features using sentiment analysis tools to score each tweet
- Build different regression models
- Compare models to see whether it can predict "retweets" and "likes" based on other features.



Lecture Review #1

- Sicilia et al. in "Twitter rumour detection in the health domain"
 - A detection system detecting rumours or non-rumour tweets in Health sector
 - Uses machine learning techniques: SVN, Nearest Neighbour, Random Forest
- Ravi in "A survey on opinion mining and sentiment analysis: Tasks, approaches and applications"
 - Comprehensive review and comparison of sentiment analysis techniques from over 300 papers
 - Result shows room for growth in intelligence-based techniques such as Random Forest



Lecture Review #2

- Carlos et al. in "Detecting and Monitoring Hate Speech in Twitter"
 - A detection system using text and emoji to detect hate speech
 - Experimented 19 different strategies of feature and classification models
 - Concluded combining LTSM and MLP-NN produces the best result
- Zubiaga et al. in "Detection and Resolution of Rumours in Social Media: A Survey"
 - Describes a rumour detection system combining: rumour detection, tracking, stance classification, and veracity classification
- In our study
 - Our dataset is relatively new (March 2020) from IEEE
 - A combination of NLP and Regression
 - Other studies uses more sophisticated tools and techniques to tackle the problem



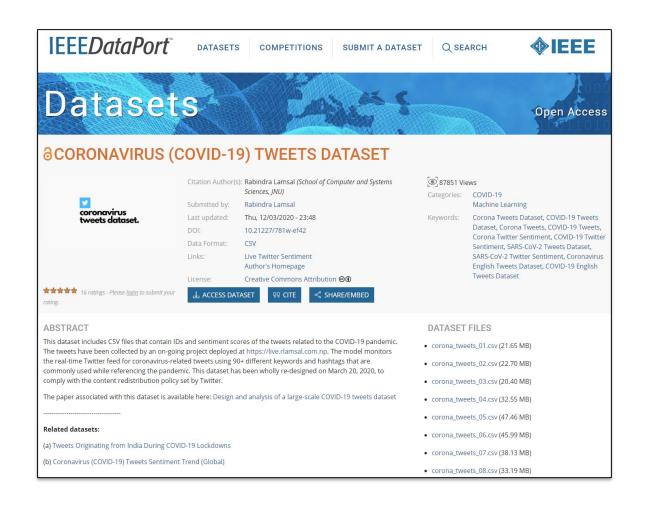
Overview of Project Approach

- Download dataset from IEEE
- 2. Load dataset onto Hydrator program convert Tweet ID to Tweets
- Extracted tweets is imported to Pandas
- 4. Perform data cleaning
- 5. Perform sentiment analysis on tweets to introduce new features
- 6. Perform basic analysis on the dataset
- Build prediction model with <u>linear regression</u>, then with k-fold
- Build prediction model with polynomial regression, then with k-fold
- Compare the results



(Pre-Python) Download dataset

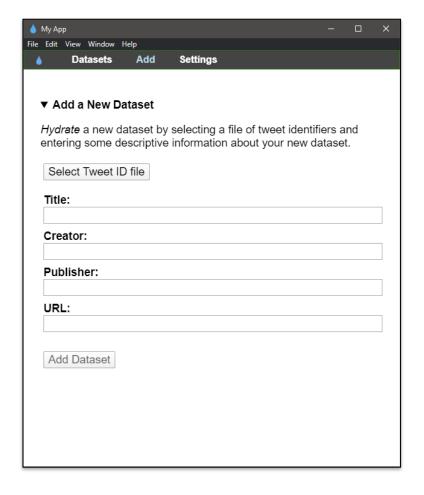
- Dataset from IEEE
 - https://ieee-dataport.org/open-access/coronavirus-covid-19-tweets-dataset
 - Since March 20, 2020
 - Updated everyday
 - Filtered 90+ COVID-19 related keywords and hashtags (https://rlamsal.com.np/keywords.tsv)
- This project uses dataset #13
 - Tweets March 31-April 1, 2020





(Pre-Python) Hydrator

- Dataset loaded to Hydrator program
 - Convert Tweet ID to Tweets using Twitter API
 - Does not need developer's account
 - Limit per 15 mins
 - Takes few hours
 - Returns multidimensional JSON
 - flatten to CSV through Hydrator
- Convert .csv dataset
 - Large in filesize
 - Can use external programs to trim features





Features Overview

Twitter API returns 35 features, and we will be using 8 features:

Feature	Description					
favorite_count	No. of "liked" this tweet has	Donardont Variables				
retweet_count	No. of retweet this tweet has Dependent Variables					
user_followers_count	No. of follower Tweet's account has					
user_statuses_count	No. of tweets and retweets this user issued					
user_favourites_count	No. of tweets this user liked					
user_followers_count	No. of followers this account has					
user_friends_count	No. of users this account follows New added feature					
user_listed_count	No. of public lists this user is a member of					
Compound	the overall sentiment score calculated; -1 is negative, 0 is neutral, 1 is positive					

Reference: Twitter Developer Documentation. (2020). Retrieve from: https://developer.twitter.com/en/docs/twitter-api/v1/data-dictionary/overview/user-object



Data Cleaning, Manipulating, and Guessing Language

- Data cleaning such as
 - Converting features to the correct data type
 - Handling null values
- Reduce noise in tweets
- Removing \n, URL, user referrals, and hashtags

 RT @Maashish81us: Live #CoronaJihad\n\nIn india , these terrorist skull caps are spreading Corona in india\n\n80% Corona Infected people are #M...

 368670 Good \nPlease always try to tweet about highlighting positive things of life. \n\nNo lise going after IK/P TI.\n\nYou can and should contribute alot more in different ways. \n\n@RehamKhan1 https://t.co/lkvY8XibLF
- Parse each tweet to filter out observations that are non-English
 - Of the 245389 tweets, 94.88% was detected as English
 - The remainder is excluded from further study

501093 @voiceaditya @ANI Infected mulla ko usi masjid me maulvi ke sath band kiya jaye. nNo need to give them any medical facilities. Let them to die by theirs itself spread corona. \nThey are doing terror activities.



Adding New Features with Sentiment Analysis

- NLTK library, SentimentIntensityAnalyzer class, polarity_score() method
- Create new features by running polarity_score() on each tweet
 - Returns a dictionary object positive, neutral, negative, compound
- Compound score is normalization of the sum of valence
 - norm_score = score/math.sqrt((score*score) + alpha)
 - "score" is computed based on some heuristics, sentiment lexicon
 - The normalized score is between -1 and 1



Reference: https://stackoverflow.com/questions/40325980/how-is-the-vader-compound-polarity-score-calculated-in-python-nltk

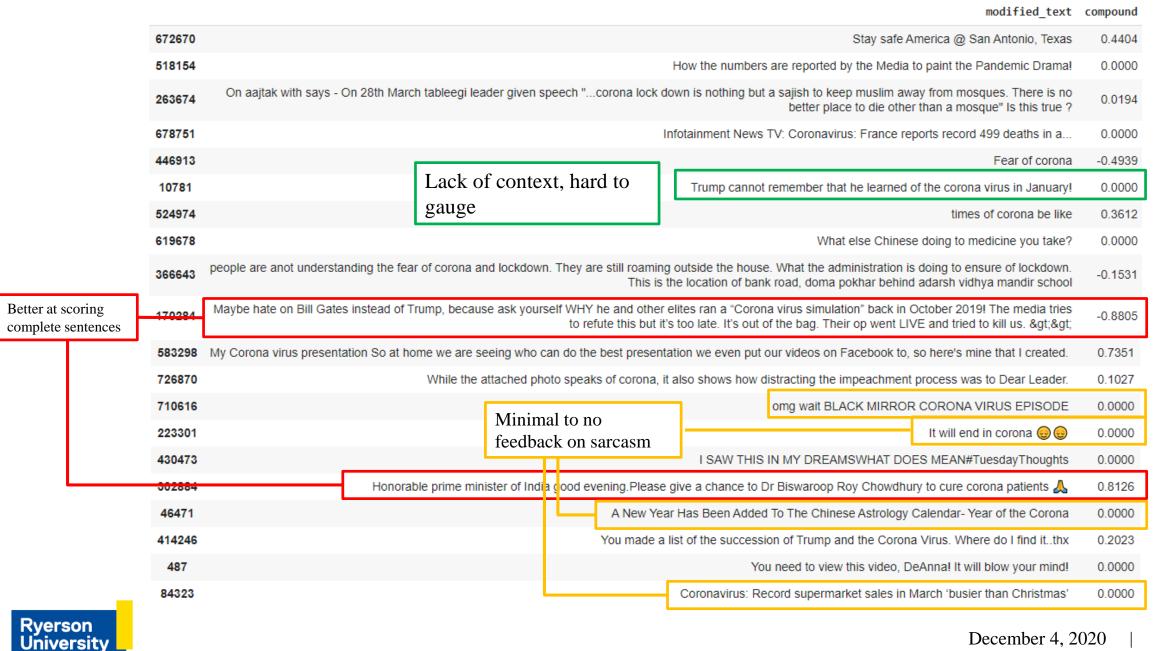


Observations from Tweets and Compound Score

- Expand the dictionary object to 4 new features
- Focus on the "compound" score feature
- Observe Tweet text and its compound score

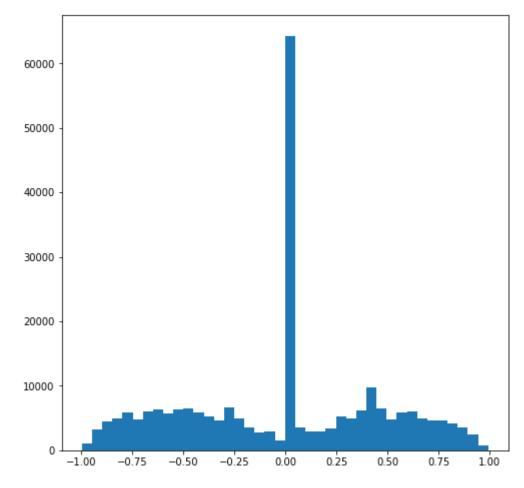


modified text compound



Observations based on the Compound feature

- SentimentIntensityAnalyzer's polarity_score Summary
 - The Good
 - Does a good job when given complete sentences for both positive or negative
 - The Bad
 - Minimal to no feedback on sarcasm
 - A lot of 0.00 scores
 - Appears to give as neutral score on texts it could not analyze
 - Individual tweets lacks context affect score
 - Some words such as "positive" can trick the algorithm



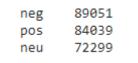
Distribution of the compound scores between -1 to 1 in 40 bins.

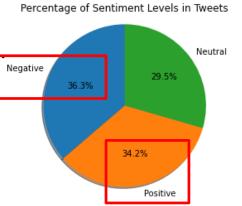


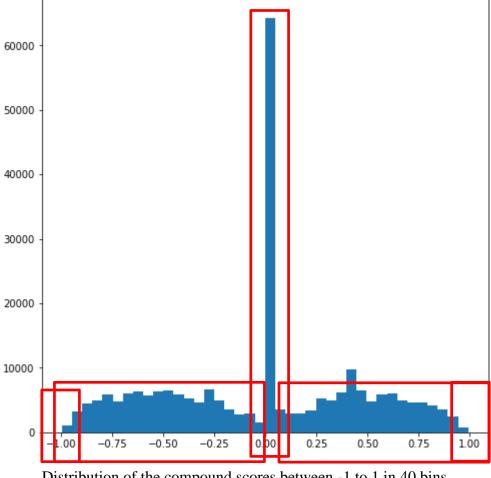
Observations based on the Compound feature

- Classification negative, neutral, positive bins based on Deo et al. research paper.
 - [-1 to -0.1][-0.1 to 0.1][0.1 to 1]
- Approx. a quarter observations in neutral range
- Extremes at -1.00 and +1.00 has the lowest count.
- Multimodal
- It is approximately symmetric
 - Just as much positive as negative

Positive and negative are about the same.







Distribution of the compound scores between -1 to 1 in 40 bins.



Deo, G. S., Mishra, A., Jalaluddin, Z. M., & Mahamuni, C. V. (2020, September). Predictive Analysis of Resource Usage Data in Academic Libraries using the VADER Sentiment Algorithm. In 2020 12th International Conference on Computational Intelligence and Communication Networks (CICN) (pp. 221-228). IEEE.

December 4, 2020

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Basic Analysis – Features Correlation

- Favorite_count and user_followers_count have high correlation
- Compound has little correlation with other features

	favorite_count	retweet_count	user_followers_count	compound	user_statuses_count	user_favourites_count	user_followers_count	user_friends_count	user_listed_count
favorite_count	1.000000	0.908576	0.165683	-0.001108	0.015366	0.007852	0.165683	0.005575	0.051646
retweet_count	0.908576	1.000000	0.090025	-0.003071	0.015991	0.007261	0.090025	0.007084	0.039251
user_followers_count	0.165683	0.090025	1.000000	0.003693	0.116452	0.000535	1.000000	0.032721	0.609057
compound	-0.001108	-0.003071	0.003693	1.000000	-0.022604	-0.028941	0.003693	-0.006560	0.000249
user_statuses_count	0.015366	0.015991	0.116452	-0.022604	1.000000	0.326723	0.116452	0.105958	0.128835
user_favourites_count	0.007852	0.007261	0.000535	-0.028941	0.326723	1.000000	0.000535	0.100920	0.016049
user_followers_count	0.165683	0.090025	1.000000	0.003693	0.116452	0.000535	1.000000	0.032721	0.609057
user_friends_count	0.005575	0.007084	0.032721	-0.006560	0.105958	0.100920	0.032721	1.000000	0.048344
user_listed_count	0.051646	0.039251	0.609057	0.000249	0.128835	0.016049	0.609057	0.048344	1.000000



Basic Analysis – Mean and Standard Deviation

• SD is relatively high which means the distribution is fairly spread out.

	favorite_count	retweet_count	${\tt user_followers_count}$	compound	user_statuses_count	user_favourites_count	${\tt user_followers_count}$	user_friends_count	user_listed_count
count	245389.00000	245389.00000	245389.00000	245389.00000	245389.00000	245389.00000	245389.00000	245389.00000	245389.00000
mean	9.52971	2.70475	9251.20519	-0.01655	27468.30799	18028.51423	9251.20519	1284.43071	34.64758
std	384.21091	122.27732	250678.23602	0.47919	75560.36124	39592.12977	250678.23602	10409.72569	680.04372
min	0.00000	0.00000	0.00000	-0.99520	1.00000	0.00000	0.00000	0.00000	0.00000
25%	0.00000	0.00000	64.00000	-0.39760	1156.00000	510.00000	64.00000	135.00000	0.00000
50%	0.00000	0.00000	331.00000	0.00000	6344.00000	4200.00000	331.00000	399.00000	1.00000
75%	1.00000	0.00000	1307.00000	0.36120	24616.00000	17807.00000	1307.00000	1038.00000	6.00000
max	108137.00000	35137.00000	62855265.00000	0.99190	4472178.00000	1254400.00000	62855265.00000	4322723.00000	202433.00000



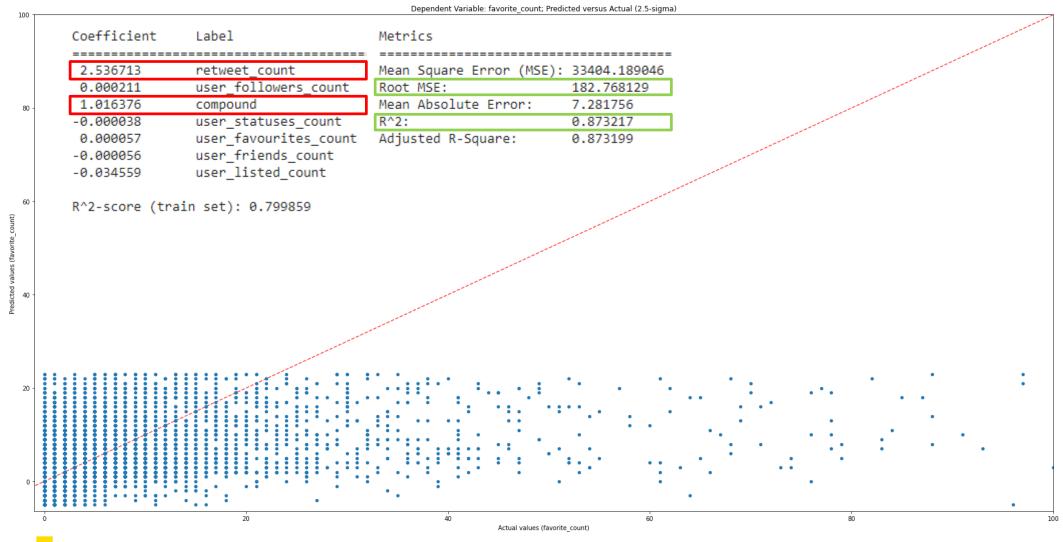
Building Different Regression Models

- Regression
 - Linear Regression 80% Train, 20% Test
 - Linear Regression in *k*-Fold (k=5)
 - Polynomial Regression, then *k*-Fold
- Two dependent variables
 - 1. favorite_count
 - 2. retweet_count

Feature	Description
favorite_count	No. of "liked" this tweet has
retweet_count	No. of retweet this tweet has
user_followers_count	No. of follower Tweet's account has
user_statuses_count	No. of tweets and retweets this user issued
user_favourites_count	No. of tweets this user liked
user_followers_count	No. of followers this account has
user_friends_count	No. of users this account follows
user_listed_count	No. of public lists this user is a member of
Compound	Sentiment score calculated between -1 to 1

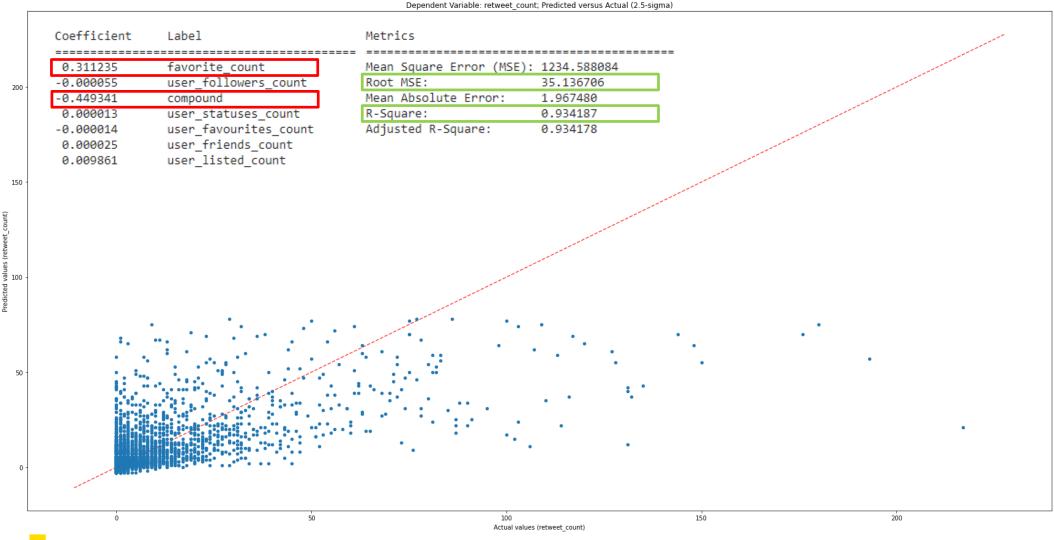


Linear Regression – "Favourite Count" as Dependent





Linear Regression – "Retweet Count" as Dependent





Linear Regression + K-fold

#1 **favorite_count**; Linear Regression + K-fold

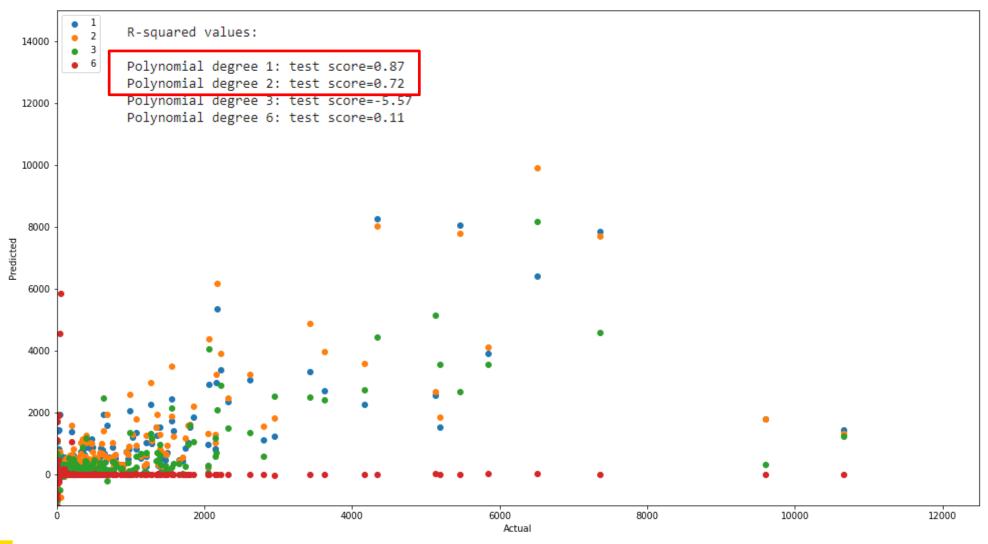
Dependent Variable: favorite count Independent Variables: ['retweet_count', 'user_followers_count', 'user_statuses_count', 'user_favourites_count', 'user_friends_count', 'user_listed_count'] K-fold: 5 MSE RMSE R-Square 31564.218170 177,663216 0.877825 Metrics 10521.044828 102.572145 0.704872 130028.329157 360.594411 0.378130 0.782832 10211.723622 101.053073 Mean Square Error (MSE): 33404.189046 0.930201 13119.346895 114.539718 Root MSE: 182.768129 Mean Absolute Error: 7.281756 Average 0.873217 Adjusted R-Square: 0.873199 39088.932535 171.284512 0.734772

#2 retweet_count; Linear Regression + K-fold

Dependent Variable: retweet count Independent Variables: ['favorite_count', 'user followers count', 'compound', 'user statuses count', 'user favourites count', 'user friends count', 'user listed count'] K-fold: 5 MSE RMSE R-Square 31.647563 1001.568224 0.945563 Metrics 798.111384 28.250865 0.605363 10974.758804 104.760483 0.685319 728.033332 26.982093 0.750776 Mean Square Error (MSE): 1234.588084 666.921016 25.824814 0.959674 Root MSE: 35.136706 Mean Absolute Error: 1.967480 Average R-Sauare: 0.934187 Adjusted R-Square: 0.934178 2833.878552 43.493164 0.789339

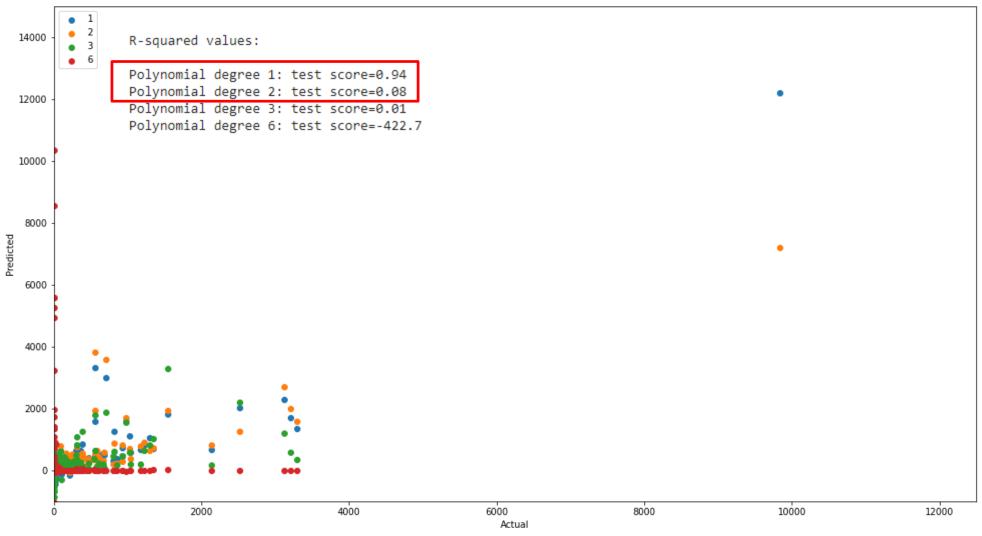


Polynomial Regression – "Favorite Count" as Dependent





Polynomial Regression – "Retweet Count" as Dependent





"Favourite Count" as Dependent; Regression Comparison Results

Polynomial Regression + K-fold Dependent Variable: favorite_count Independent Variables: ['retweet_count', 'user_followers_count', 'compound', 'user_statuses_count', 'user_verified' K-fold: 5 Polynomial R-Square Degree 1: 176.1003309179579 0.88 Degree 2: 283.8671924780902 0.69 Degree 3: 906.2368606263769 -2.18 Degree 6: 856.3979925552468 -1.84Degree 1: 101.57117876732413 0.71 Degree 2: 113.61553501192776 0.64 Degree 3: 164.8107158447843 0.24 1067.8173629126154 Degree 1: 361.7648735168686 0.37 -0.6 Degree 2: 578.1225176563707 Degree 3: 10089.810890024544 -485.89 38011377.335343964 -6910168447.01 Linear Regression + K-fold Degree 1: 0.76 106.07747474685985 132.28407898975604 0.63 Degree 2: Degree 3: 429.9725980224988 -2.93 Independent Variables: ['retweet count', 'user followers count', 'compound', 'user statuses count', 'user favourites count', 'user friends count', 'user listed count' Degree 6: 21654.500707596068 -9971.23 K-fold: 5 RMSE R-Square Degree 1: 113.14836415856713 0.93 Degree 2: 284.245851156108 0.57 31564.218170 177,663216 0.877825 Degree 3: 1548.2663280761865 -11.75 10521.044828 102.572145 0.704872 Degree 6: 15713.147572038102 -1312.61 130028.329157 360.594411 0.378130 10211.723622 101.053073 0.782832 Degree Average RMSE Average R^2 13119.346895 114.539718 0.930201 171.732444 0.730000 2627.819479 -100.502000 --------7610133.839796 -1382035952.734000 39088.932535 171.284512 0.734772



"Retweet Count" as Dependent; Regression Comparison Results

Polynon	mial Regression +	+ K-fold	
K-fold: 5	ables: ['favorite_count', 'user_f		'user_statuses_count', 'user_verified']
Polynomial	Root MSE	R-Square	
Degree 1:	30.619157472439177	0.95	
Degree 2:	143.57465611146827	-0.12	
Degree 3:	197.92059429558387	-1.13	
Degree 6:	140.91449714880363	-0.08	
Degree 1:	27.778555948274388	0.62	
Degree 2:	33.17703268992806	0.46	
Degree 3:	44.99600146557491	-0.0	
Degree 6:	1595.006459641652	-1256.94	
Degree 1:	105.01778633851833	0.68	
Degree 2:	109.10569803537199	0.66	
Degree 3:	1123.4793102354063	-35.19	
Degree 6:	185441.21308761396	-986024.03	7 7 7 7 7 7 7 7 7 7 7 7 7 7 7 7 7 7 7 7
Degree 1:	28.269222892920038	0.73	Linear Regression + K-fold
Degree 2:	47.405288929894574	0.23	
Degree 3:	55.005669883911004	-0.04	Dependent Variable: retweet_count
Degree 6:	10069.950456869094	-34712.13	Independent Variables: ['favorite_count', 'user_followers_count', 'compound', 'user_statuses_count', 'user_favourites_count', 'user_followers_count', 'user_fold: 5
D	25.580491200820568	0.06	MSE RMSE R-Square
Degree 1: Degree 2:	73.46282149176497	0.96 0.67	
Degree 3:	73.46282149176497 241.73438207411132	-2.53	1000.984587 31.638340 0.945595
Degree 6:	5081.564815280062	-2.53 -1560.37	798.111384 28.250865 0.605363
Degree 6:	3001.304013200002	-1500.57	10974.758804 104.760483 0.685319
Degree Average RM	RMSE Average R^2	·	726.632995 26.956131 0.751255
1 43.453043			668.976723 25.864584 0.959550
2 81.345099			1.
3 332.62719			Average
6 40465.729			2833.892899 43.494081 0.789416
			2833.892899 43.494001 0.794410



Conclusion

- Regression models were somewhat able to predict Retweet-ability (Retweet count) and Likeability (Favorite_count)
- Linear Regression produced slightly better results, at less resource cost
- Compound feature contributed to the prediction
- We can say that "a tweet's sentimentality and other features have some influence on the tweet's retweet-count and liked-counts"

Further Studies

- Use classification instead of regression approach
 - Use categorical instead of continuous value for sentiment score
- Conduct research on the 3 sentiment groups (negative, neutral, positive) independently
 - The 3 groups might have its own regression fit
- Group by user's screen name and calculate each user's mean sentiment score
 - Research whether there are any effects on number of followers and number of favourite tweets against a user's mean sentiment score

