Applied Network Science: Social Media Networks

Presenting
"Negativity Spreads More than Positivity on Twitter after both Positive and Negative Political Situations"
by Schöne et al. (2021)

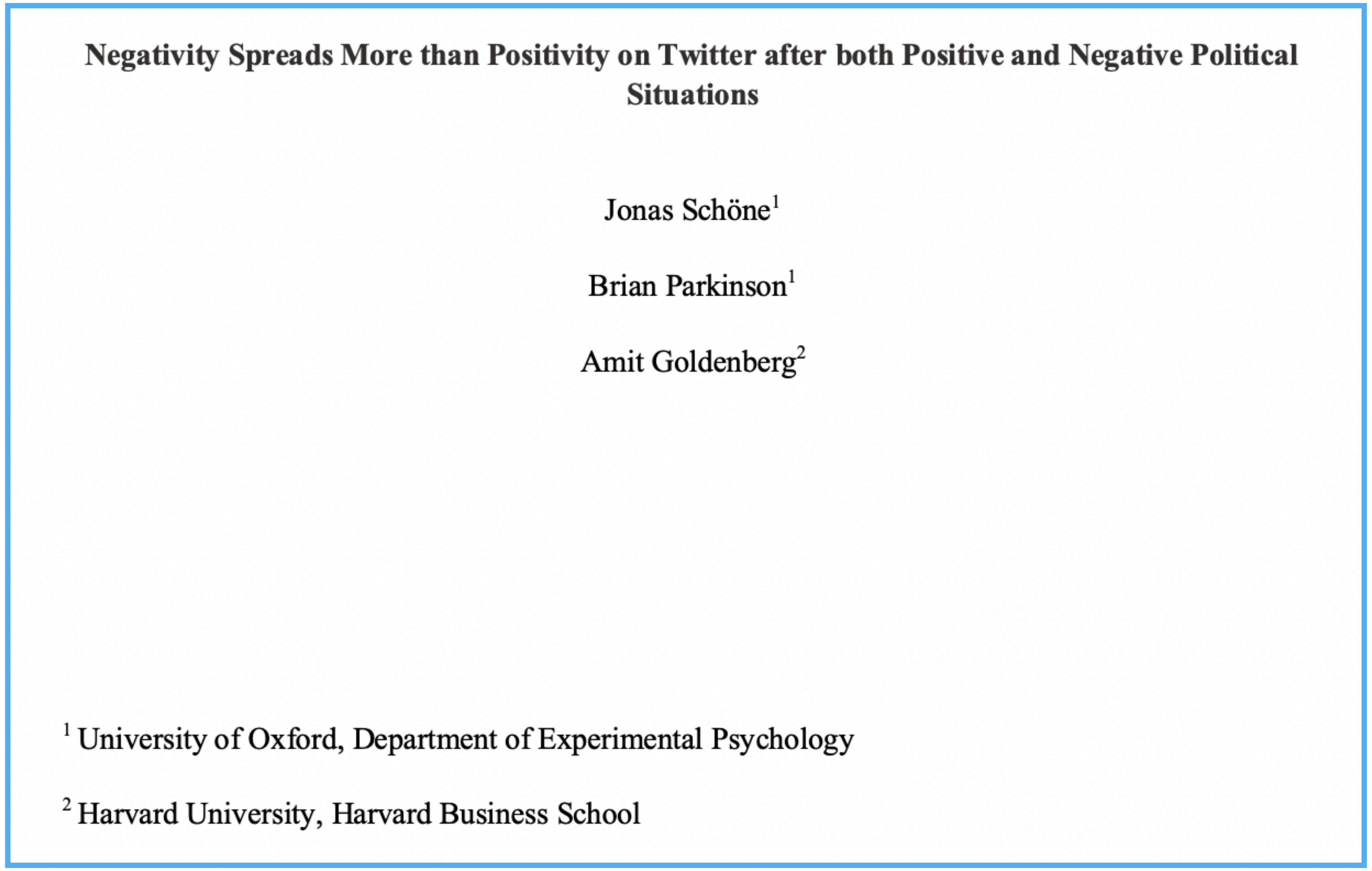
Alexander Timans & Samuel Anzalone

10. December 2021

Agenda

1. Presenting the assigned paper
    1.1. General approach and hypothesis
    1.2. Analysis steps (4) and results
2. Our analysis of the paper and dataset
    2.1. Insights, points of critique and possible improvements
    2.2. Additional visualizations

Paper overview



Negativity Spreads More than Positivity on Twitter after both Positive and Negative Political Situations

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- Paper: https://psyarxiv.com/x9e7u/
- Data and Code: https://osf.io/xqevy/files/

- Latest version from May 2021
- Not yet published (pre-print)
- Topic related to Sentiment Analysis
- Twitter data (4 datasets)
- Same analysis approach to two studies with two datasets each
- Code in R

Paper research setting

Research Q: What kind of emotional language drives content sharing on Twitter in both positive and negative political situations?

Hypothesis: In negative situations, content with negative emotional language will be shared more. In positive situations no hypothesis.

Study 1: same political event

- US elections 2016
- Positive situation: Trump victory
- Negative situation: Hillary loss

Study 2: different political events

- Positive situation: US Supreme Court ruling for same-sex marriage (2015)
- Negative situation: Ferguson Unrest after shooting of Michael Brown (2014)

Study 1: Dataset overview

- **Data:** tweets within 7 days of election result based on hashtags
- Trump victory: #PresidentTrump, #TrumpWinner, #MakeAmericaGreatAgain, #MAGA, #TrumpWon, #Trump2020; ~340 000 tweets
- Hillary loss: #TrumpRiot, #TrumpProtest, #ProtestTrump, #NotMyPresident, #HesNotMyPresident, #AntiTrump; ~280 000 tweets
- Applied **SentiStrength** sentiment analysis classifier (Thelwall et al., 2010) to obtain positive (1 to 5) and negative (-1 to -5) sentiment scores for each tweet
- Tweet texts in separate dataset so cannot match them to other information :-(

Study 1: Sample Trump tweets

	user_id	tweet_id	retweets	likes	followers	time	sen_pos	sen_neg	binary_affiliation
0	ATWYMOVRZP	RULEKCGZNF	0	2	20919	2016-11-09 18:43:58	0	3	NaN
1	JARDVQKMGH	ASVFDYRELQ	0	0	402	2016-11-09 16:06:59	1	0	NaN
2	GCUZERVKIS	NOFDYISPBE	0	0	2053	2016-11-11 05:25:50	0	0	NaN
3	XUQCRKIFBS	EMLDKOBYVH	0	0	879	2016-11-09 00:08:06	2	0	NaN
4	VXINQMGRPC	BXQEAPZDYL	0	0	175	2016-11-11 00:46:31	0	0	NaN
...	...	...	...	...	...	...	...	...	...
278183	DUFQXYRJVN	FSBPDHGXLV	0	0	0	2016-11-15 22:11:47	0	0	NaN
278184	OJSDFZQCXR	ESTPJOXHYC	0	0	0	2016-11-15 21:14:15	0	0	NaN
278185	ZEYLSTJPNW	ZIDJXNPLWC	0	0	2	2016-11-15 22:21:15	3	0	NaN
278186	OYUHVXWRPI	YLHMDFQION	0	0	0	2016-11-15 23:51:22	0	0	NaN
278187	NaN	GMWPJYXKZF	0	1	498	2016-11-10 17:47:01	0	1	NaN

278188 rows × 9 columns

Study 1: Sample Trump tweets text

	retweets	tweet_body	tweet_body_lemmatized	valence
0	1	Hear that MAGA The guy advising you on your r...	hear that maga the guy advise you on your reti...	-1
1	1	Hear that MAGA https tco 4MB2J22RwU	hear that maga https tco 4mb2j22rwu	0
2	0	Hear that MAGA https tco ytfwcmrM8a	hear that maga https tco ytfwcmrm8a	0
3	1	draintheswamp indeed Hear that MAGA Hes selli...	draintheswamp indeed hear that maga hes sell y...	0
4	0	Got that MAGA https tco AXfmBBWmNV	get that maga https tco axfmbbwmnv	0
...	...	...	...	...
405402	0	Todays a good day to stay off social medialet ...	today a good day to stay off social medialet a...	-2
405403	2	Boy was I wrong about this election Hopefully ...	boy be i wrong about this election hopefully t...	-1
405404	1	First time millennial voter for realDonaldTrum...	first time millennial voter for realdonaldtrum...	0
405405	0	Great job arizona presidenttrump	great job arizona presidenttrump	2
405406	0	my teacher wanted killary and now she wont sta...	my teacher want killary and now she wont stand...	1

405407 rows × 4 columns

Paper analysis approach

1. Valence of the situation

- Checking that situations assumed are indeed positive/negative ("sanity check")
- In essence statistical comparison of means of neg. and pos. sentiment scores

2. Predicting the spread of emotional language

- Predicting retweets with the pos. and neg. sentiment scores among covariates
- Statistical model: Linear Mixed Model

3. Political affiliation of users

- Classifying users as "Rep" or "Dem" based on simple heuristic
- (Try to) show that results from **2.** are due to intra-group and not inter-group dynamics

4. Text analysis

- Group tweets into two topics (positive/negative) via Latent Dirichlet Allocation
- Identify most unique uni-/bigrams for each topic via occurrence likelihood scores

Analysis 1: Valence of the situation

1. Valence of the situation

- Checking that situations assumed are indeed positive/negative ("sanity check")
- In essence statistical comparison of means of neg. and pos. sentiment scores

Results:

- For tweets celebrating Trump victory, mean of **positive** sentiment score higher; statistically significant (at 95% confidence)
- For tweets celebrating Hillary’s loss, mean of **negative** sentiment score higher; statistically significant (at 95% confidence)
- "Sanity check" satisfied

Analysis 2: Predicting the spread of emotional language

2. Predicting the spread of emotional language

- Predicting retweets with the pos. and neg. sentiment scores among covariates

- Statistical model: Linear Mixed Model
- Linear regression that handles both fixed and random effects
- Analogy regression formula: `y ~ x1 + x2`

Model formula shape:

```
retweets ~ sen_pos + sen_neg + sen_pos:sen_neg + followers + (1|user_id)
```

Analysis 2: Predicting the spread of emotional language

```
Linear mixed model fit by REML. t-tests use Satterthwaite's method [lmerModLmerTest
]
Formula: retweets ~ sen_pos + sen_neg + sen_pos:sen_neg + scale(followers_log) +
    (1 | user_id)
   Data: d.trump

REML criterion at convergence: 3676786

Scaled residuals:
   Min     1Q Median     3Q    Max
 -5.52  -0.04  -0.01   0.01 334.80

Random effects:
 Groups   Name        Variance Std.Dev.
 user_id  (Intercept)   758.5   27.54
 Residual             31513.9  177.52
Number of obs: 278187, groups:  user_id, 115920

Fixed effects:
                      Estimate   Std. Error           df t value
(Intercept)            3.79731      0.55860 191382.54134   6.798
sen_pos                0.87098      0.51817 270614.21003   1.681
sen_neg                0.06651      0.46371 271288.38826   0.143
scale(followers_log)   9.12517      0.38886  80904.97826  23.467
sen_pos:sen_neg       -0.53829      0.47262 274154.74054  -1.139
                                 Pr(>|t|)
(Intercept)                0.0000000000106 ***
sen_pos                             0.0928 .
sen_neg                             0.8859
scale(followers_log) < 0.0000000000000002 ***
sen_pos:sen_neg                     0.2547
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

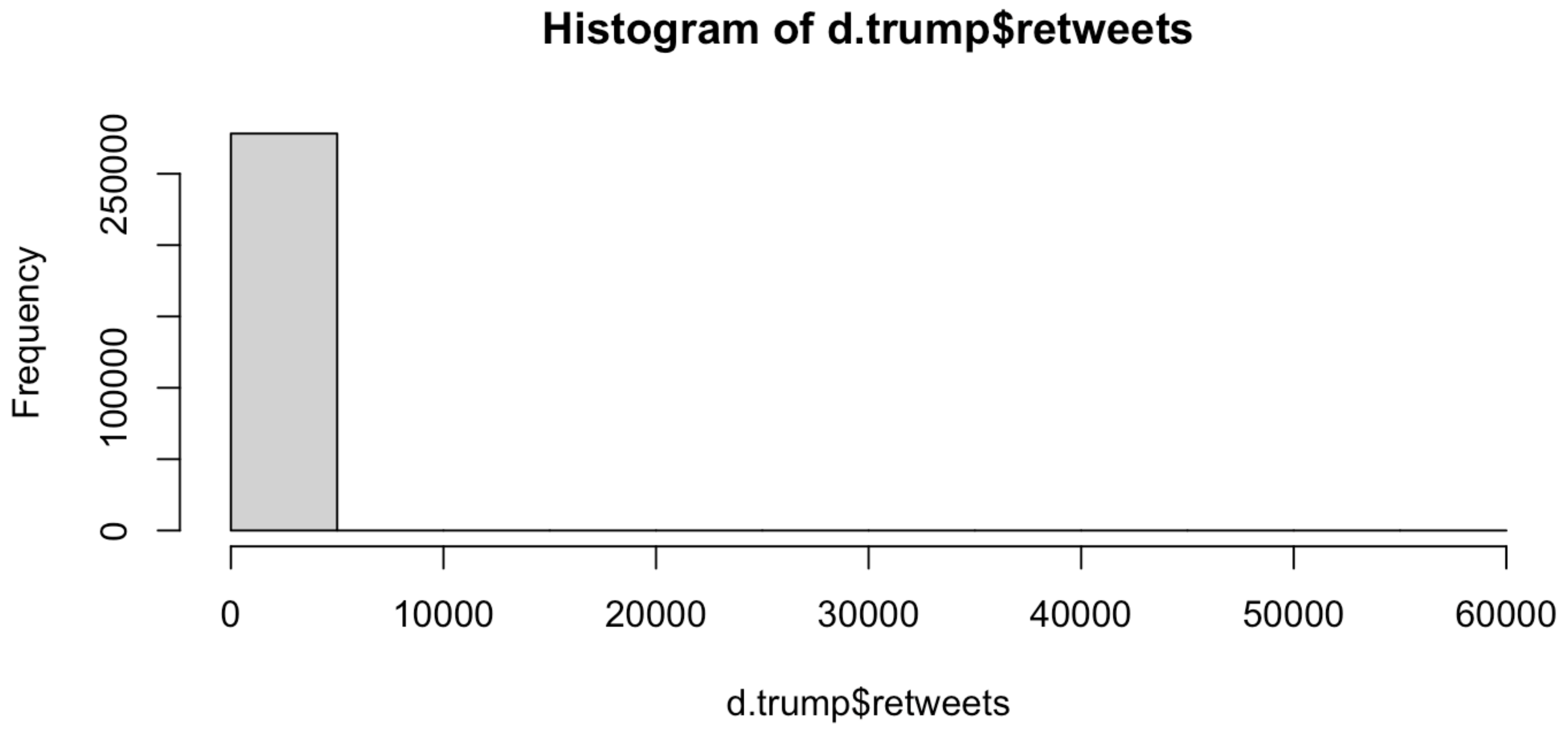
Model: `retweets ~ sen_pos + sen_neg + sen_pos:sen_neg + followers + (1|user_id)`

Data: Trump victory tweets

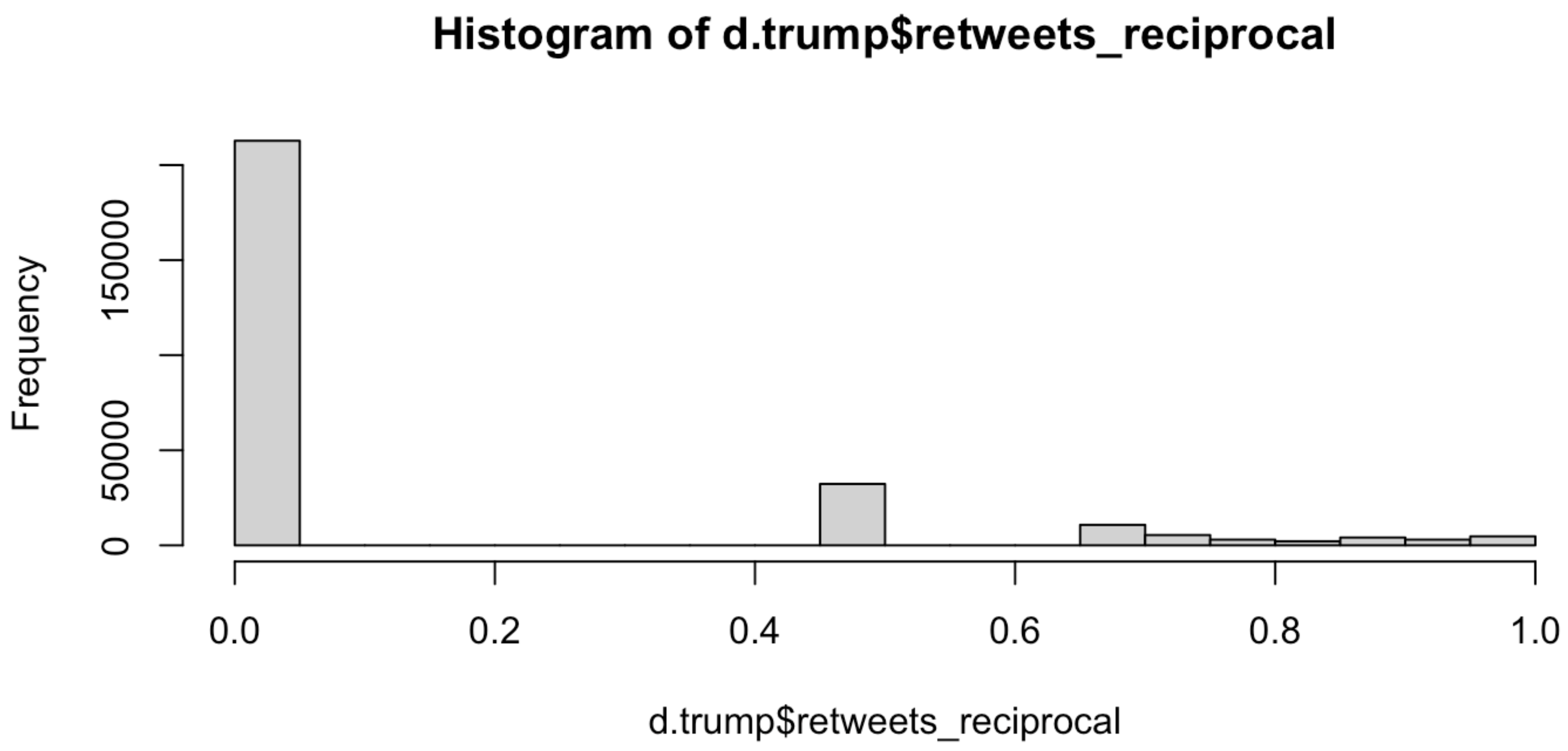
Covariates	**Significant at 95%**
Intercept	**Yes**
sen_pos	No
sen_neg	No
sen_pos:sen_neg	No
followers	**Yes**

Analysis 2: Predicting the spread of emotional language

- Extreme skewness of data



- Transform: $f(x) = 1 - (x+1)^{-1}$

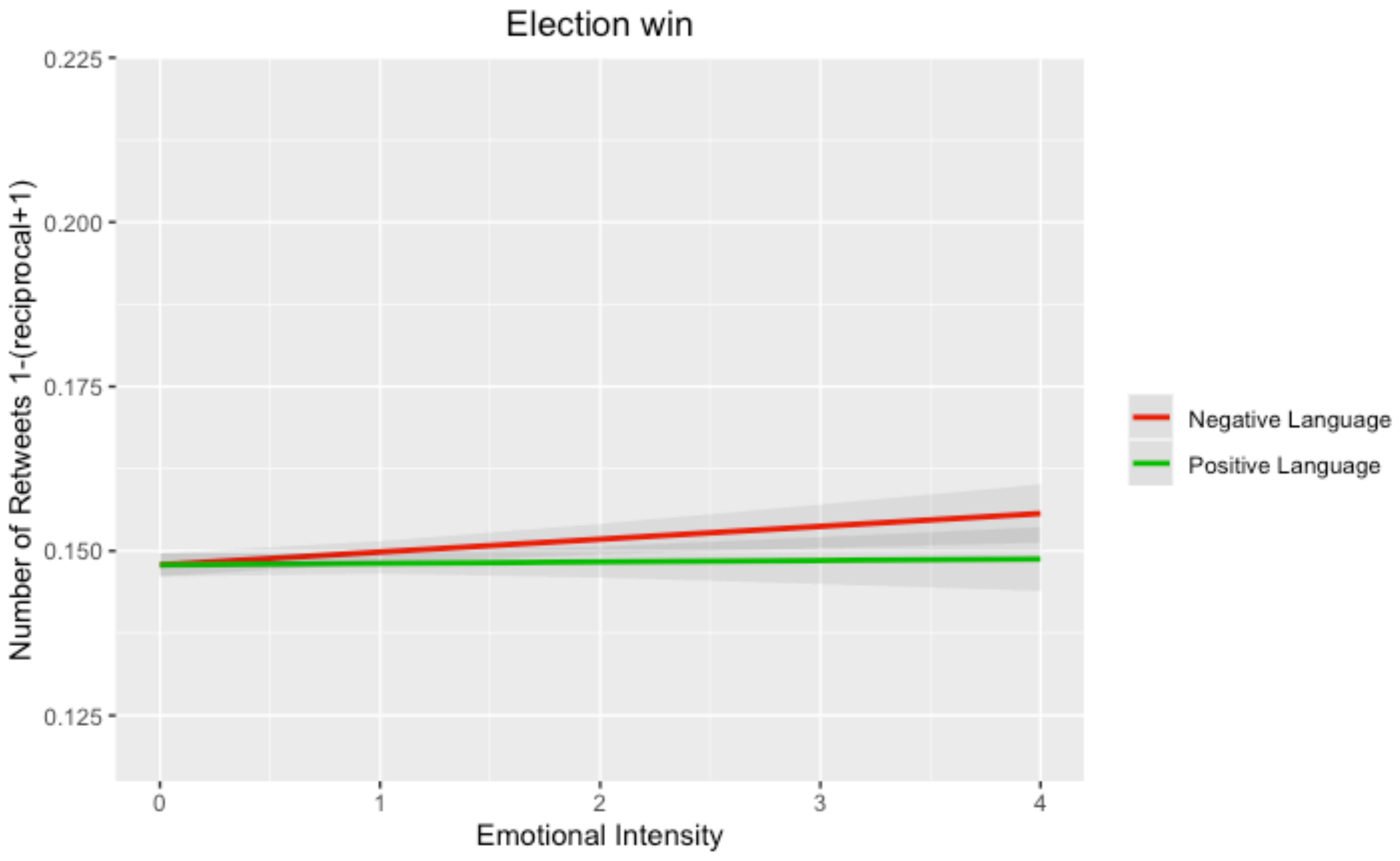


Analysis 2: Predicting the spread of emotional language

Model: `retweets_reciprocal ~ sen_pos + sen_neg + sen_pos:sen_neg + followers + (1|user_id)`

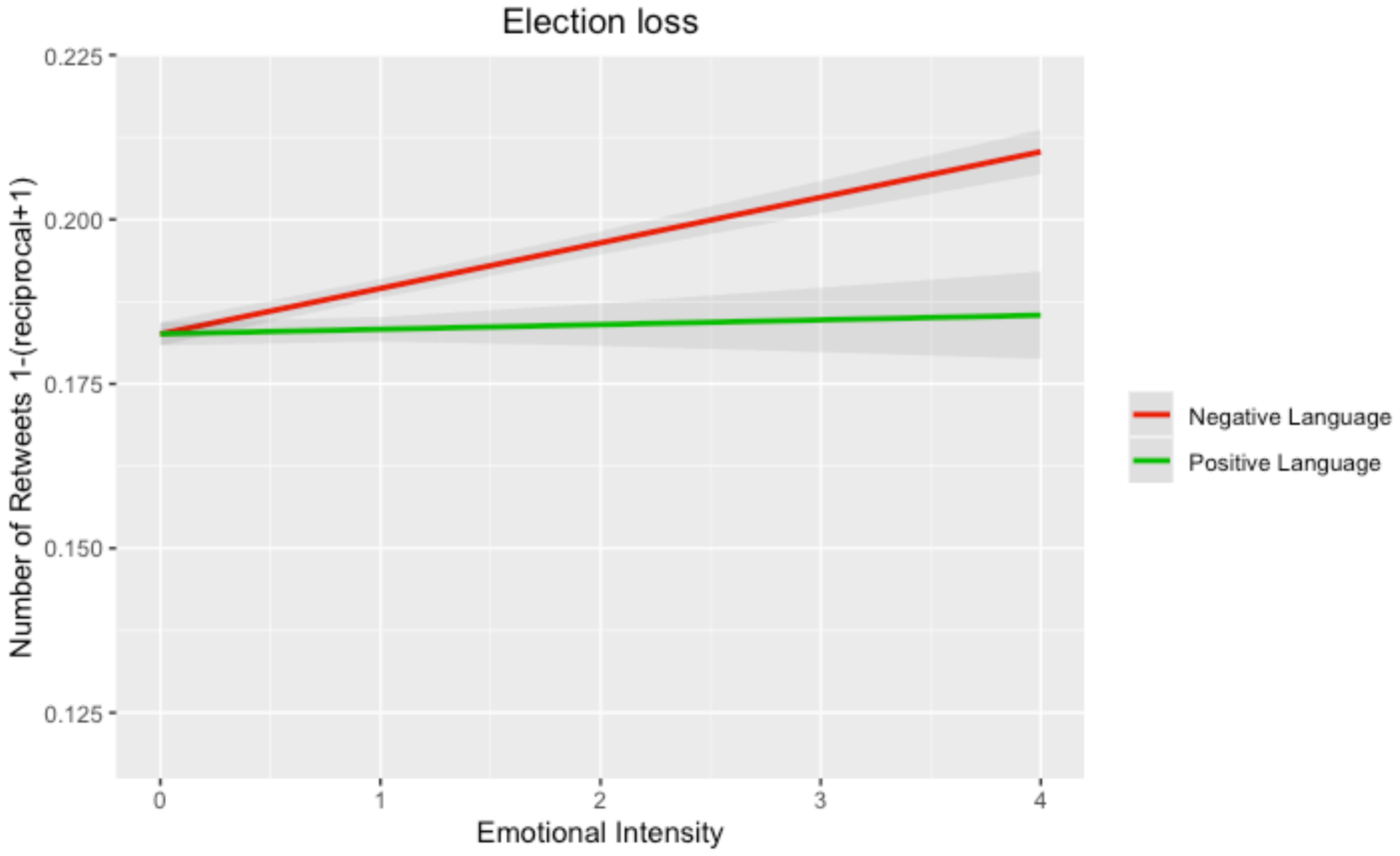
- Trump victory tweets:

Covariates	Significant at 95%
`Intercept`	**Yes**
`sen_pos`	No
`sen_neg`	**Yes**
`sen_pos:sen_neg`	No
`followers`	**Yes**



- Hillary loss tweets:

Covariates	Significant at 95%
`Intercept`	**Yes**
`sen_pos`	No
`sen_neg`	**Yes**
`sen_pos:sen_neg`	No
`followers`	**Yes**



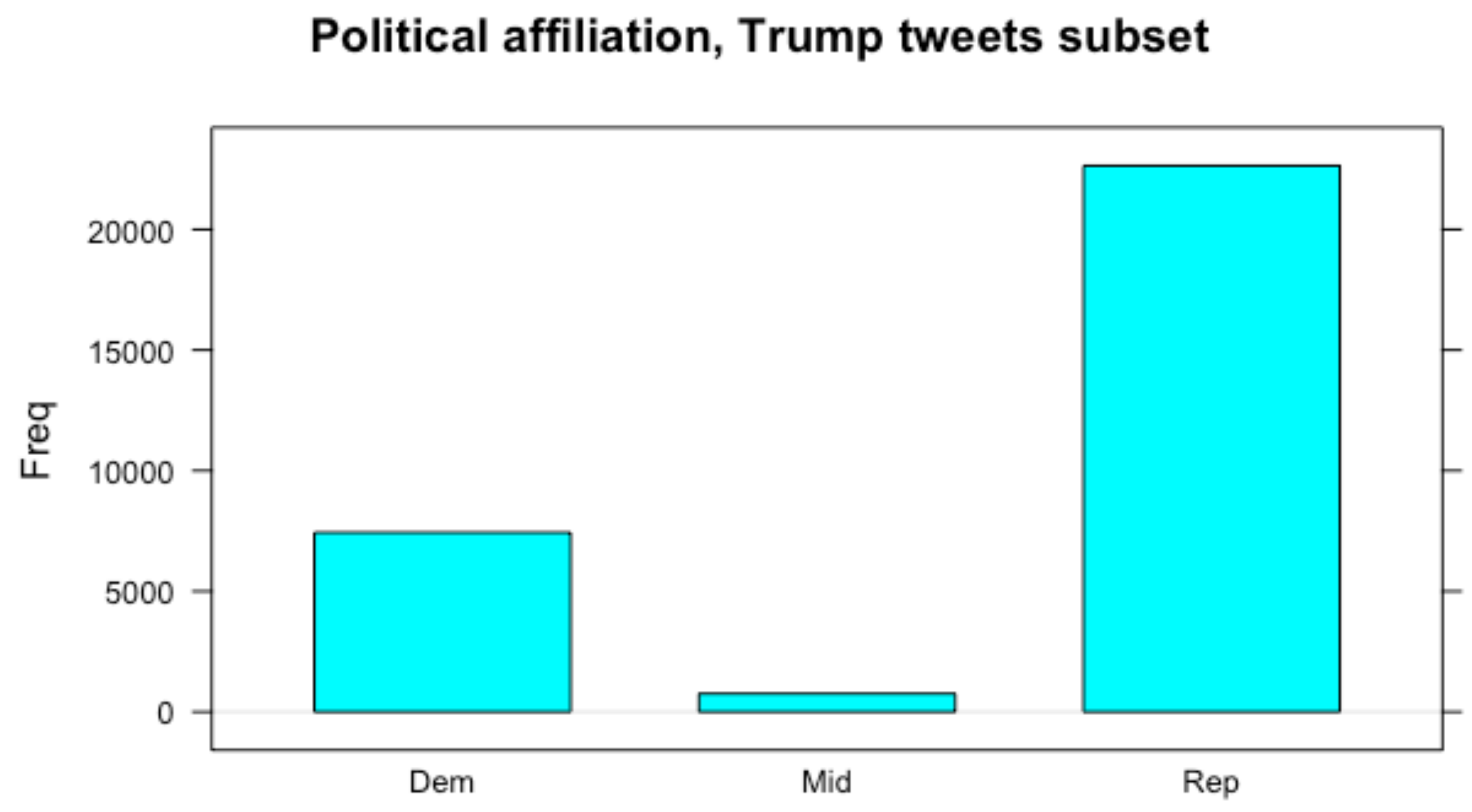
Analysis 3: Political affiliation of users

3. Political affiliation of users (for Trump tweets)

- Classifying users as "Rep" or "Dem" based on simple heuristic
- (Try to) show that results from **2.** are due to intra-group and not inter-group dynamics

- Assign binary affiliation to subset of tweets
- Assignment based on how many political figures of each political camp are followed
- List of ~4200 political figures from Bail et al. (2018)
- Heuristic: $max(\#Rep, \#Dem)$
- ~73 % Rep, ~27 % Dem, thus claim negative tweets predominantly written by Republicans —> intra-group

```
> count(d.trump$binary_affiliation)
     x    freq
1  Dem    7433
2  Mid     755
3  Rep   22642
4 <NA> 247358
```



Analysis 4: Text analysis

4. Text analysis (for Trump tweets text)

- Group tweets into two topics (positive/negative) via Latent Dirichlet Allocation
- Identify most unique uni-/bigrams for each topic via occurrence likelihood scores

- LDA generates topics based on co-occurence of uni-/bigrams and sentiment

- Two topics clearly identified (topic association values $\gamma > 99.9\,\%$)

topic 1 (positive tweets):				topic 2 (negative tweets)			
Unigrams	$\log_2(\frac{\beta 1}{\beta 2})$	Bigrams	$\log_2(\frac{\beta 1}{\beta 2})$	Unigram	$\log_2(\frac{\beta 1}{\beta 2})$.	Bigrams	$\log_2(\frac{\beta 1}{\beta 2})$.
hope	151.11	wow electionnight	129.53	#tcot	-221.24	USA trumptrain	-134.95
Donald	148.22	Reince MAGA	128.17	liberal	-220.56	war trump	-134.40
love	147.41	sweet patriot	127.68	media	-219.82	beat Hillary	-133.46
happy	147.39	beautiful baby	127.22	lie	-219.32	time ago	-133.21
awesome	147.39	follow god	126.10	hate	-219.26	civil war 2	-133.02

Our analysis: critique, improvements and data insights

- **Insight #1:** Quality of dataset
- **Insight #2:** Accuracy of SentiStrength sentiment analysis tool
- **Insight #3.1:** Coding error in Linear Mixed Model analysis
- **Insight #3.2:** Linear Mixed Model use questionable (Trump tweets)
- **Insight #4:** Naive political affiliation assignment (Trump tweets)
- **Insight #5:** Implementation of text analysis raises questions

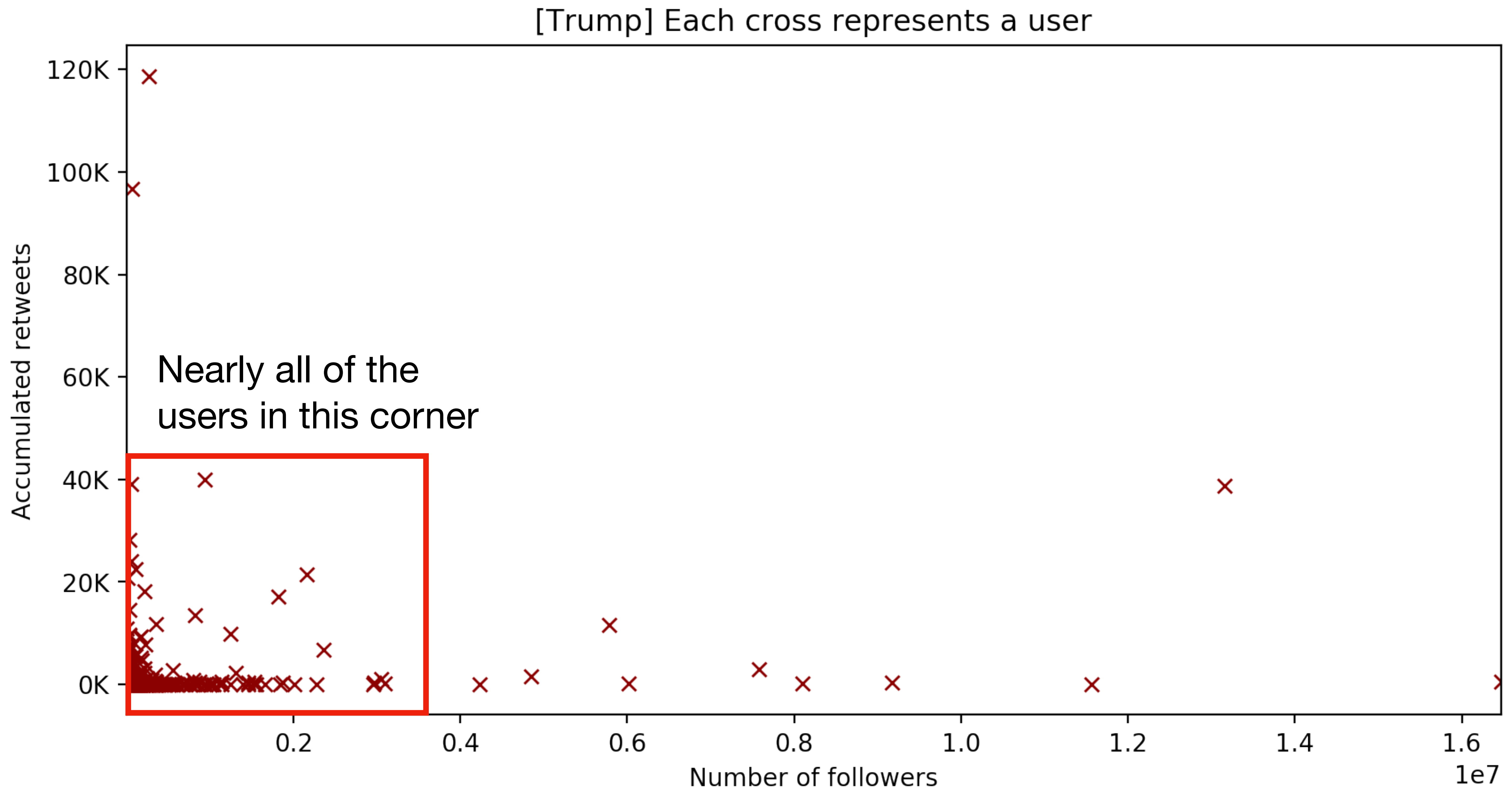
Insight #1: Quality of dataset – Skewness

- Few users with millions of followers, most people under 300
- Some users went "viral"
- But the majority of users did not accumulate any like or retweet at all

Dataset Trump					
Per user stat	min	max	mean	median	std.
Followers	0	16.468.857	3.174,3	253	94.125,2
Acc. likes	0	171.168	19,3	1	967,6
Acc. retweets	0	118.697	10,4	0	541

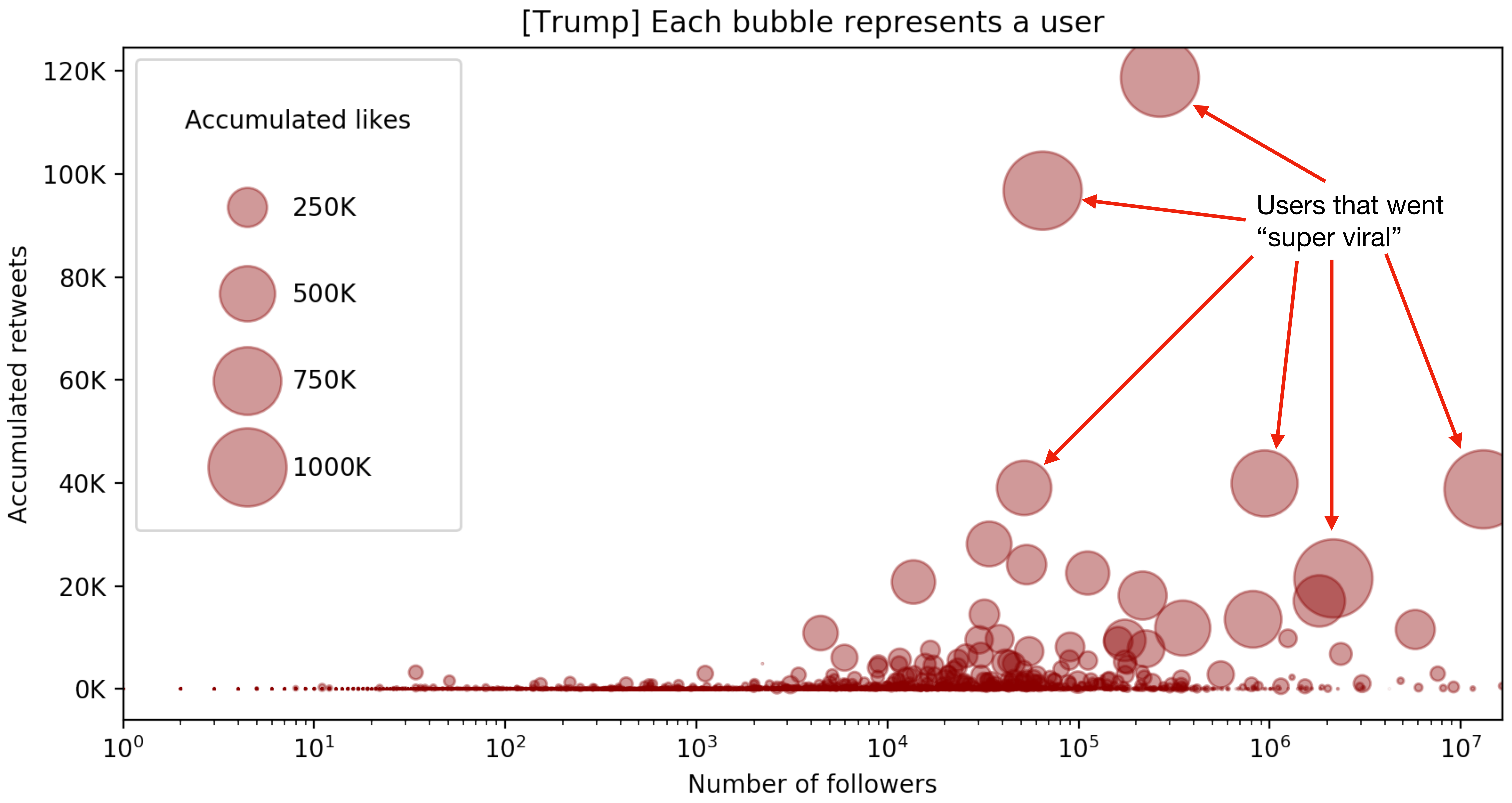
Insight #1: Quality of dataset – Skewness

- Thus as noted by authors in the paper, the dataset is really skewed

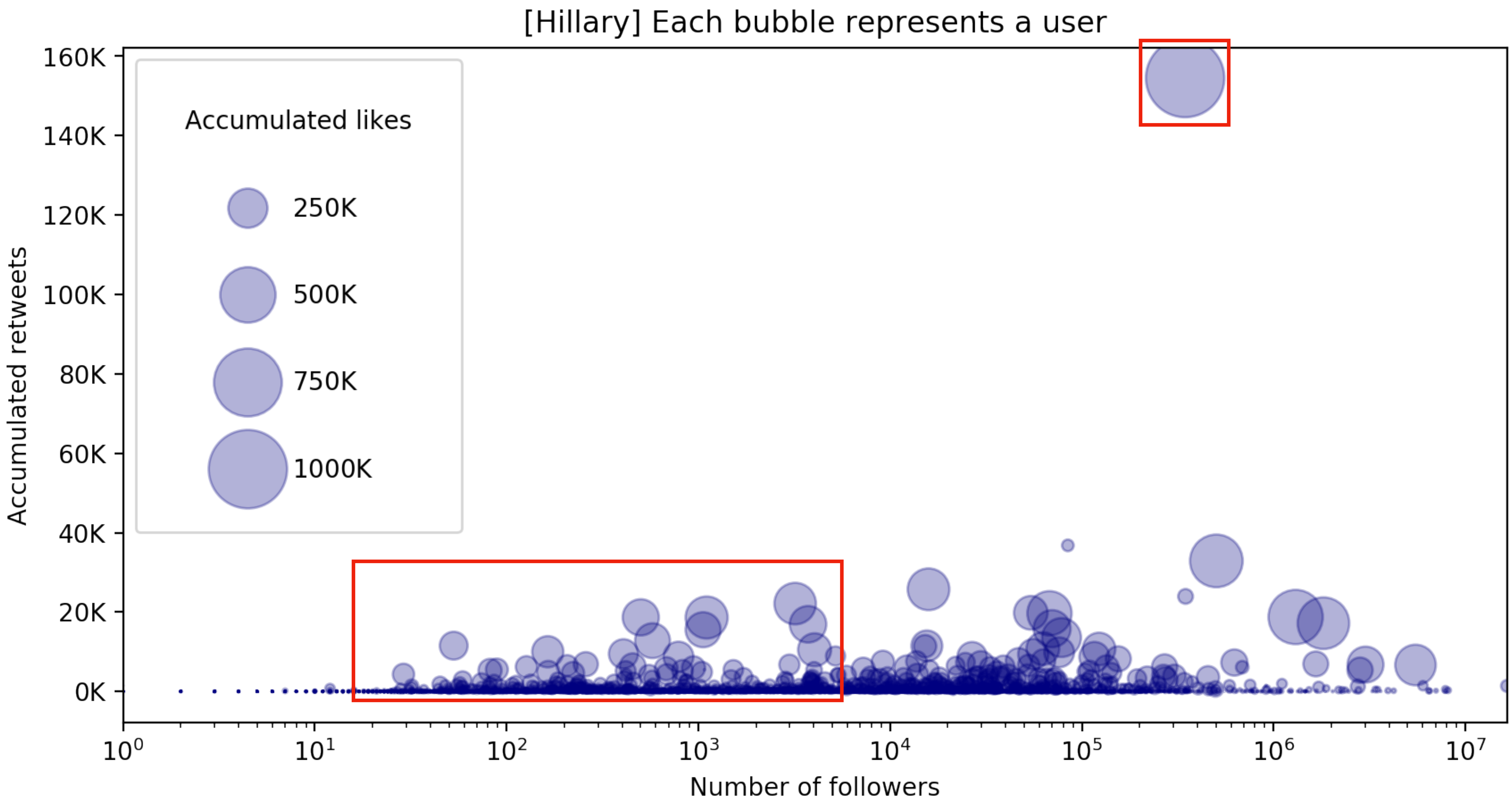


- The following exploratory visualizations will thus be **log-scaled** in the number of followers

Insight #1: Quality of dataset – Skewness

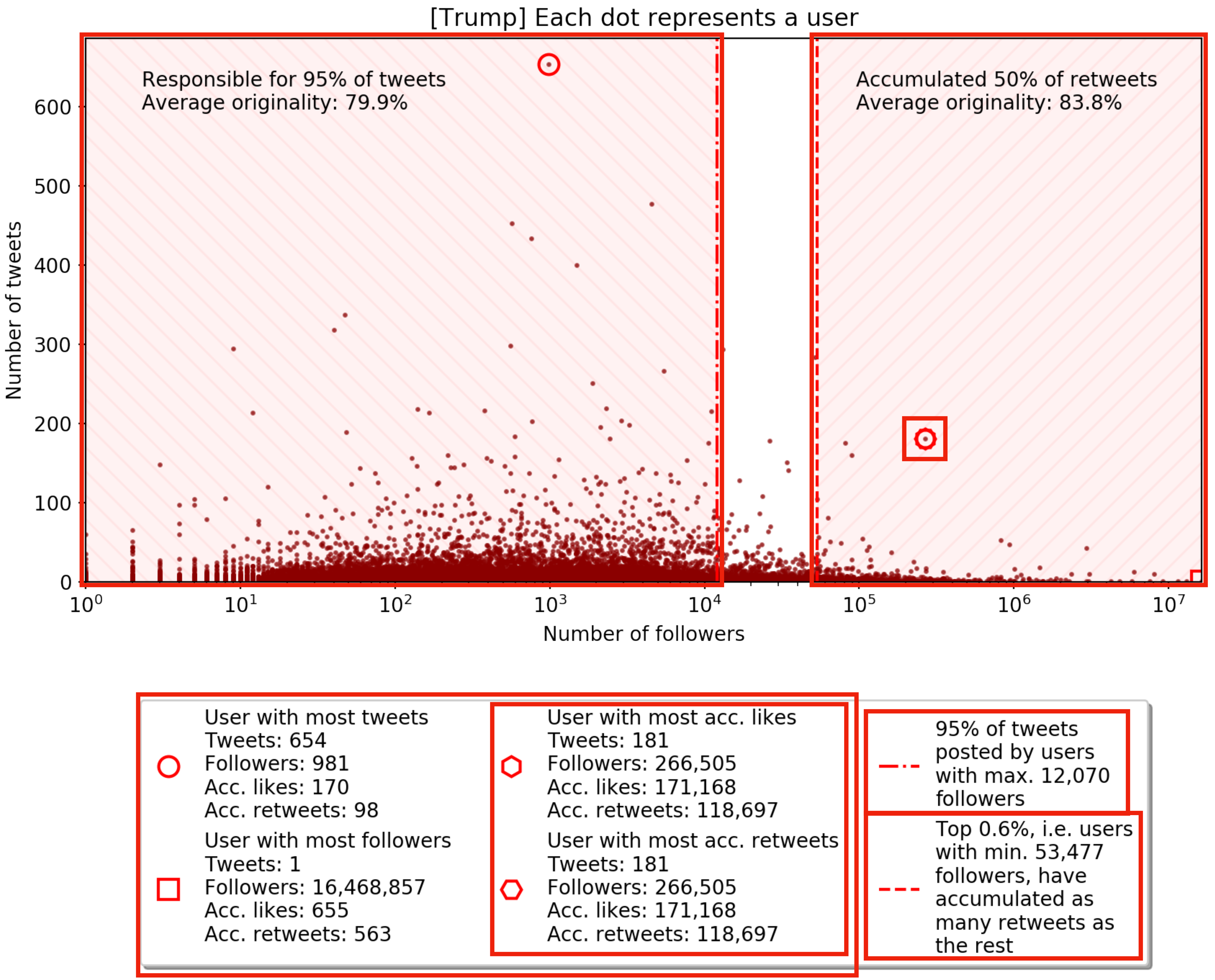


Insight #1: Quality of dataset – Skewness



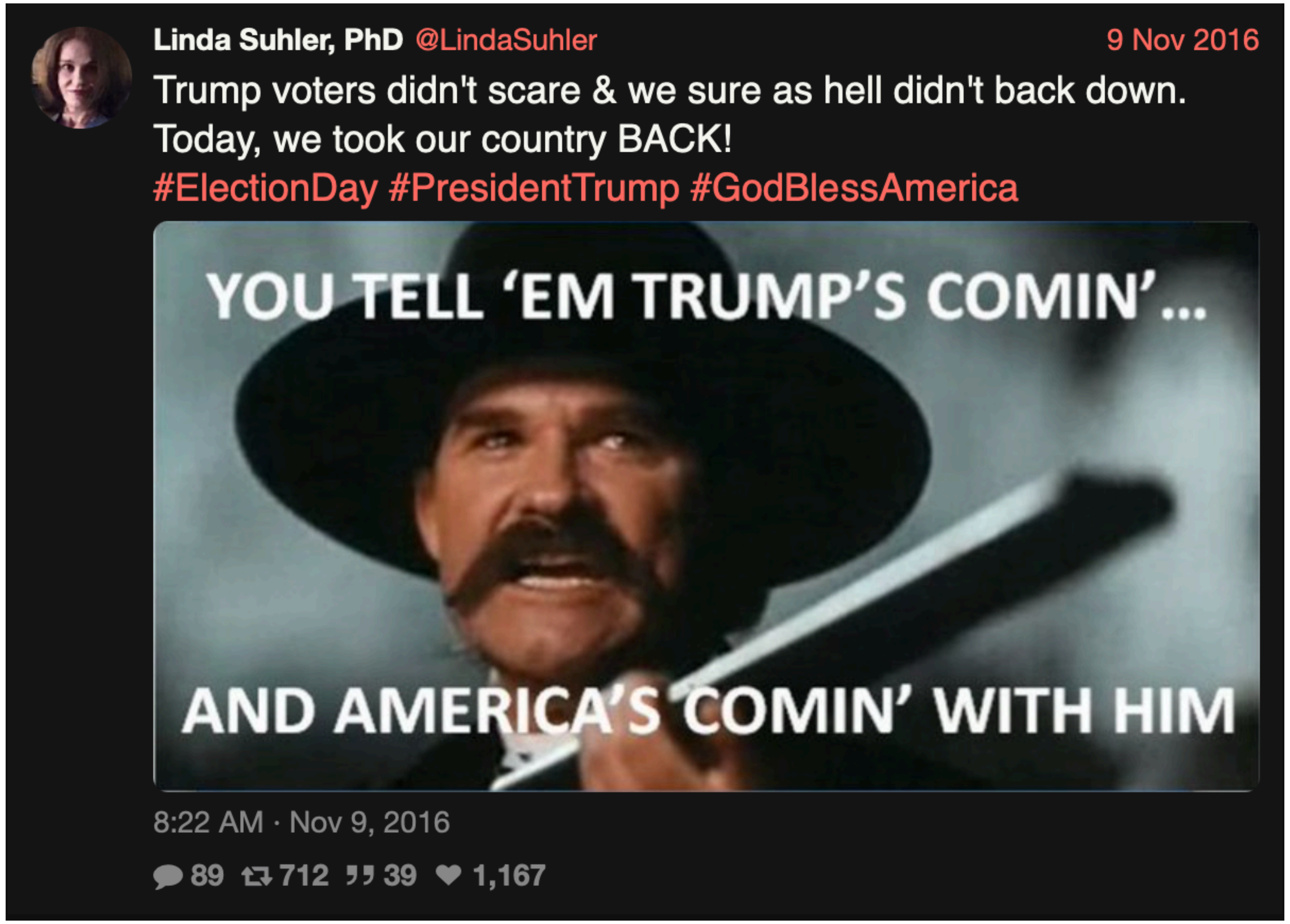
Insight #1: Quality of dataset – Retweet responsibility

- Analysis of who bears responsibility for the retweets
- Lower 99%, w.r.t. followers, of users are responsible for 95% of tweets
- Top 0.6%, w.r.t followers, of users are responsible for 50% of the accumulated retweets
- Some “outliers” and their per user statistics are listed below
- “Outlier” most acc. likes = “outlier” most acc. retweets



Insight #1: Quality of dataset – Retweet responsibility

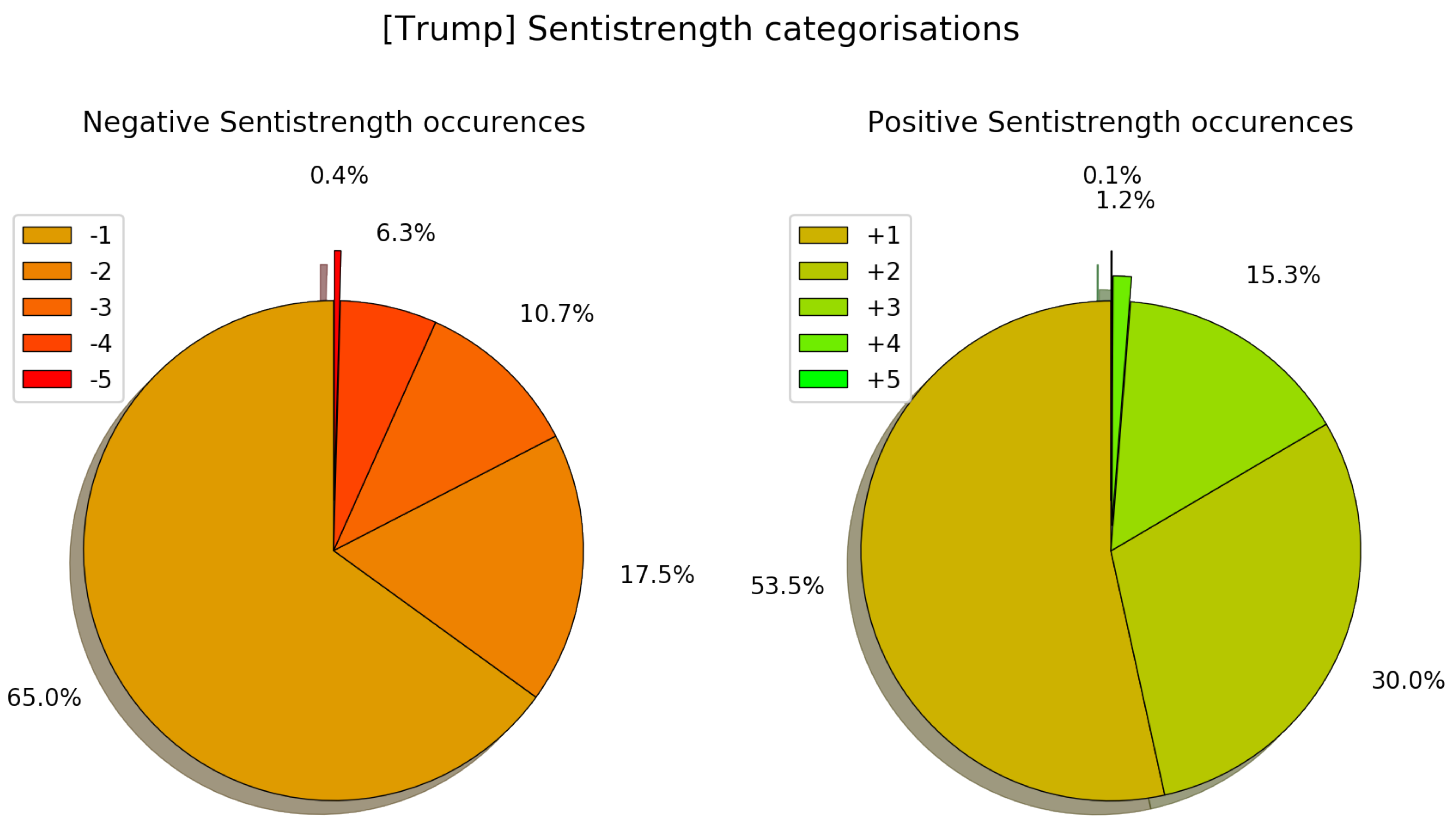
- Meet **Linda Suhler, PhD**, a paid hack, our most acc. likes & retweets "outlier"
- Science article "Election polling is in trouble" writes the following:
- *"One of the most influential pro-Trump tweeters of all […] was Linda Suhler [a paid hack]. The internet has no record of that person and direct Twitter messages from Science were never answered"*



Insight #1: Quality of dataset – Anonymity

- The authors did indeed anonymise the tweet and user IDs …
- … but did not remove the attached links
- Example: “`Tweet #192923:  Those red areas are inhabited by folks who love the Second Amendment Grow up MAGA` **`https tco 7f6ndo5WSh`**”
- This is a Twitter short URL, which links to the attachment of the tweet

Insight #2: SentiStrength



Insight #2: SentiStrength

Example of false “negative”

- Identified sentiment category: **-3**
- SentiStrength sees key words **hate** and **poison**
- In reality is a message of **hope and solidarity**

Insight #2: SentiStrength

Example of false "positive"

- Original tweet: `Those red areas are inhabited by folks who` **`love`** `the Second Amendment`
- Identified sentiment category: **+3**
- SentiStrength sees key word "love"
- In reality it is a **threat** meant for liberals

Insight #2: SentiStrength

- Ribero et al. (2016) paper
- Cited by authors to justify use of SentiStrength as adequate
- "*… its [SentiStrength's] coverage is usually low as this method tends to classify a high number of instances as neutral*"
- Zimbra et al. (2016) algorithm based on dynamic NNs achieves high accuracy for a 5-class sentiment classification on Twitter data

Table 13 Mean rank table for datasets of social

3-classes			2-classe
Pos	Method	Mean Rank	Pos
1	Umigon	2.57	1
2	LIWC15	3.29	2
3	VADER	4.57 (4.57)	3
4	AFINN	5.00	4
5	Opinion Lexicon	5.57	5
6	Semantria	6.00	6
7	Sentiment140	7.00	7
8	Pattern.en	7.57	8
9	SO-CAL	9.00	9
10	Emolex	12.29	10
11	SentiStrength	12.43 (11.60)	11
12	Opinion Finder	13.00	12

Table 8 Mean rank table for all datasets

3-classes		
Pos	Method	Mean Rank
1	VADER	4.00 (4.17)
2	LIWC15	4.62
3	AFINN	4.69
4	Opinion Lexicon	5.00
5	Semantria	5.31
6	Umigon	5.77
7	SO-CAL	7.23
8	Pattern.en	9.92
9	Sentiment140	10.92
10	Emolex	11.38
11	Opinion Finder	13.08
12	SentiWordNet	13.38
13	Sentiment140_L	13.54
14	SenticNet	13.62
15	SentiStrength	13.69 (13.71)
16	SASA	14.77

Table 7. Class-level recall for five-class sentiment classification

Sentiment Class	DAN2	SVM	Repustate
Strongly Positive	87.59%	84.30%	40.20%
Mildly Positive	66.67%	61.40%	9.02%
Mildly Negative	87.01%	65.60%	21.93%
Strongly Negative	85.07%	91.10%	17.65%

Insight #3.1: Coding error in Linear Mixed Model analysis

- To obtain `retweets` use incorrect backtransform from `retweets_log`
- $x_{log} = log(x+1) \iff x = exp(x_{log}) - 1$
- Instead authors use $x = exp(x_{log} - 1)$
- Since it doesn't always return integers, apply rounding…
- Model results don't drastically change, but values in model pipeline do change

```
df_h_agg <- df_h %>% # THIS IS THE SOLUTION
  dplyr::group_by(user_id) %>%
  dplyr::summarise(sen_neg = mean(sen_neg),
            sen_pos = mean(sen_pos),
            retweets_log = mean(retweets_log),
            followers = mean(followers),
            followers_log = max(followers_log),
            retweets = round(mean(exp(retweets_log - 1))))
```

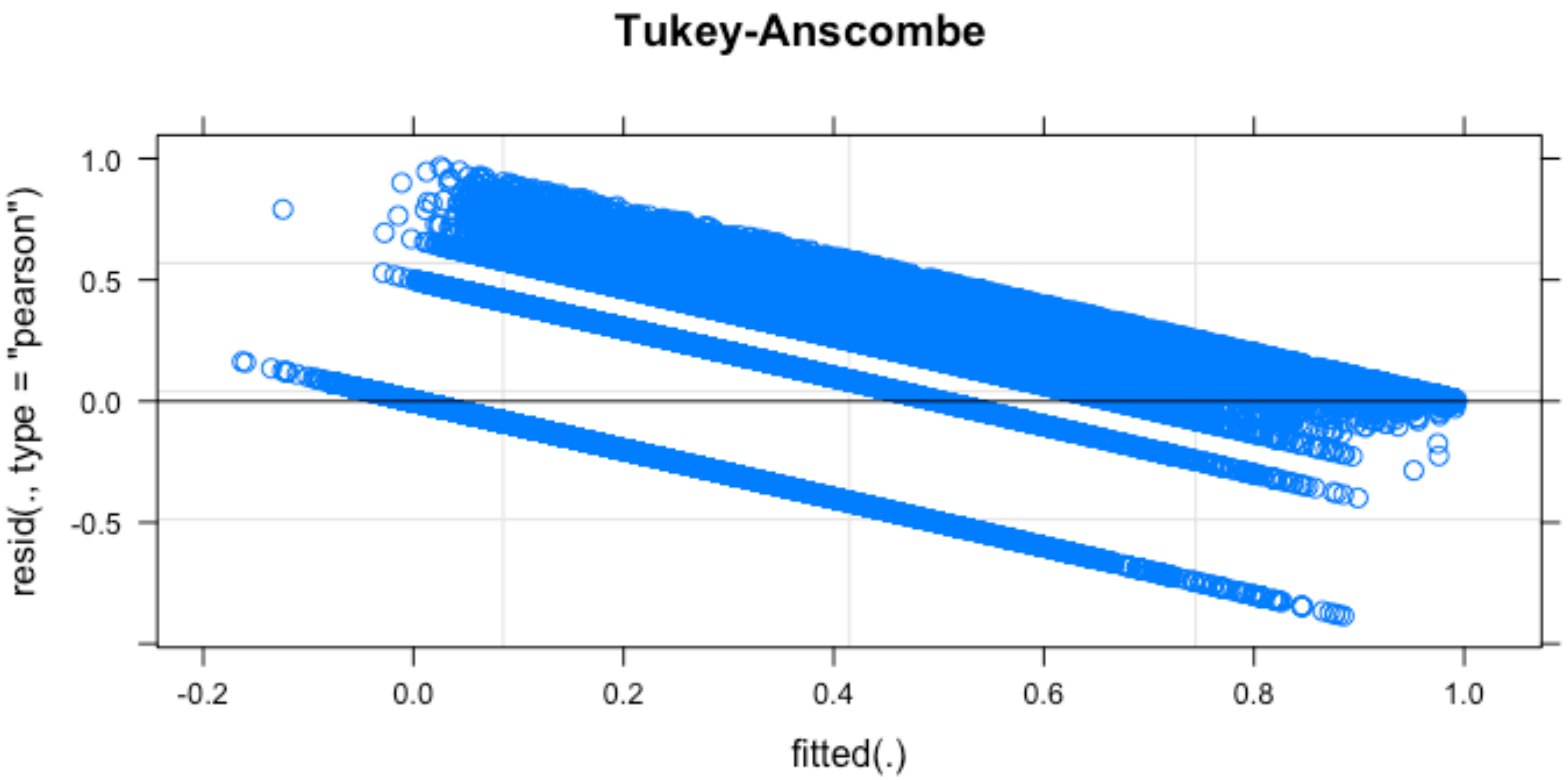
retweets	retweets_exp1	retweets_reciprocal	retweets_reciprocal_exp1	retweets_log
53	20	0.9814815	0.9523810	3.9889840
86	32	0.9885057	0.9696970	4.4659081
0	0	0.0000000	0.0000000	0.0000000
39	15	0.9750000	0.9375000	3.6888795
0	0	0.0000000	0.0000000	0.0000000
124	46	0.9920000	0.9787234	4.8283137
0	0	0.0000000	0.0000000	0.0000000
5	2	0.8333333	0.6666667	1.7917595

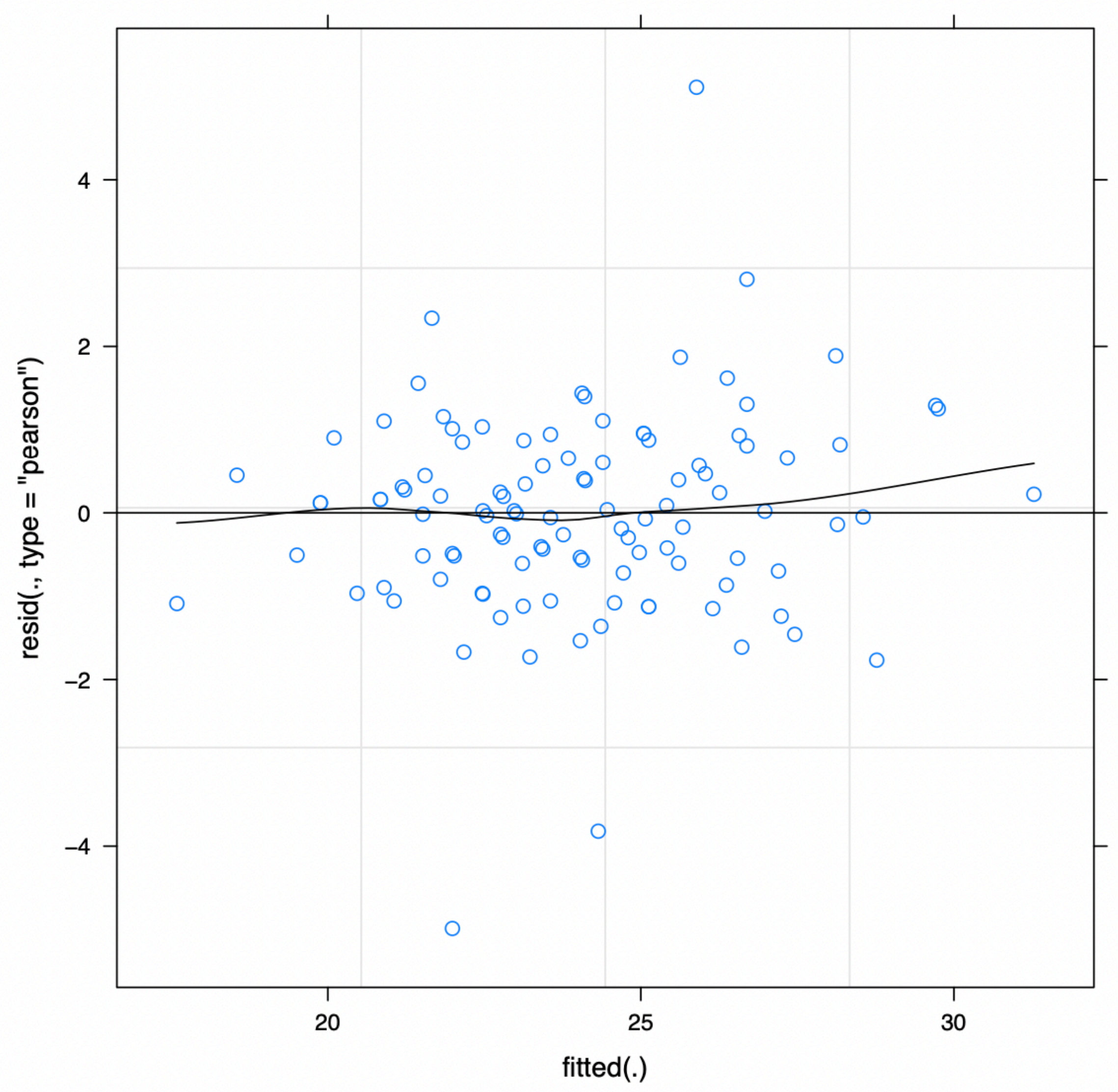
Insight #3.2: Linear Mixed Model use questionable

- No mention of **checking model assumptions** or challenging selected model

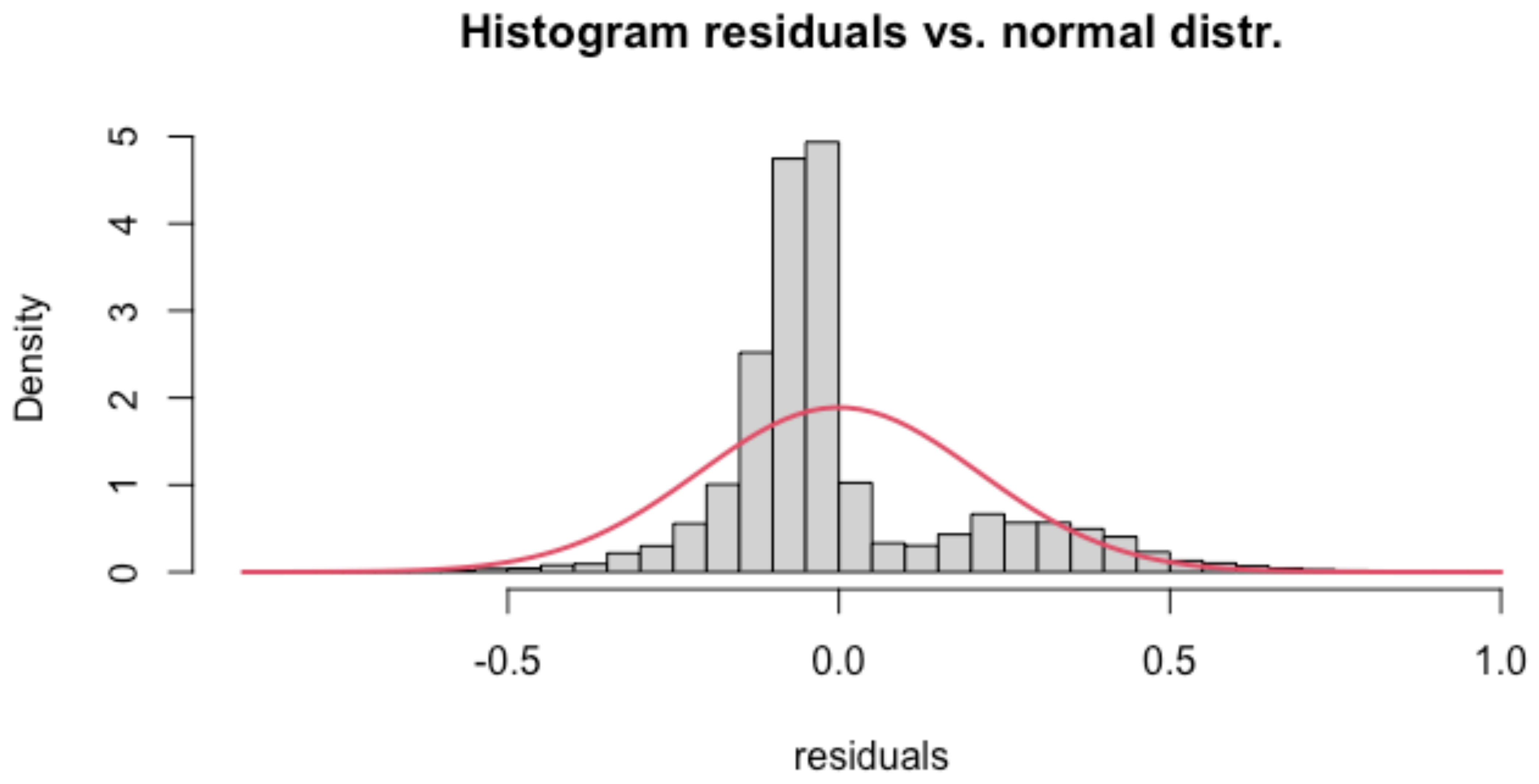
Among others, Linear Mixed Model assumes:

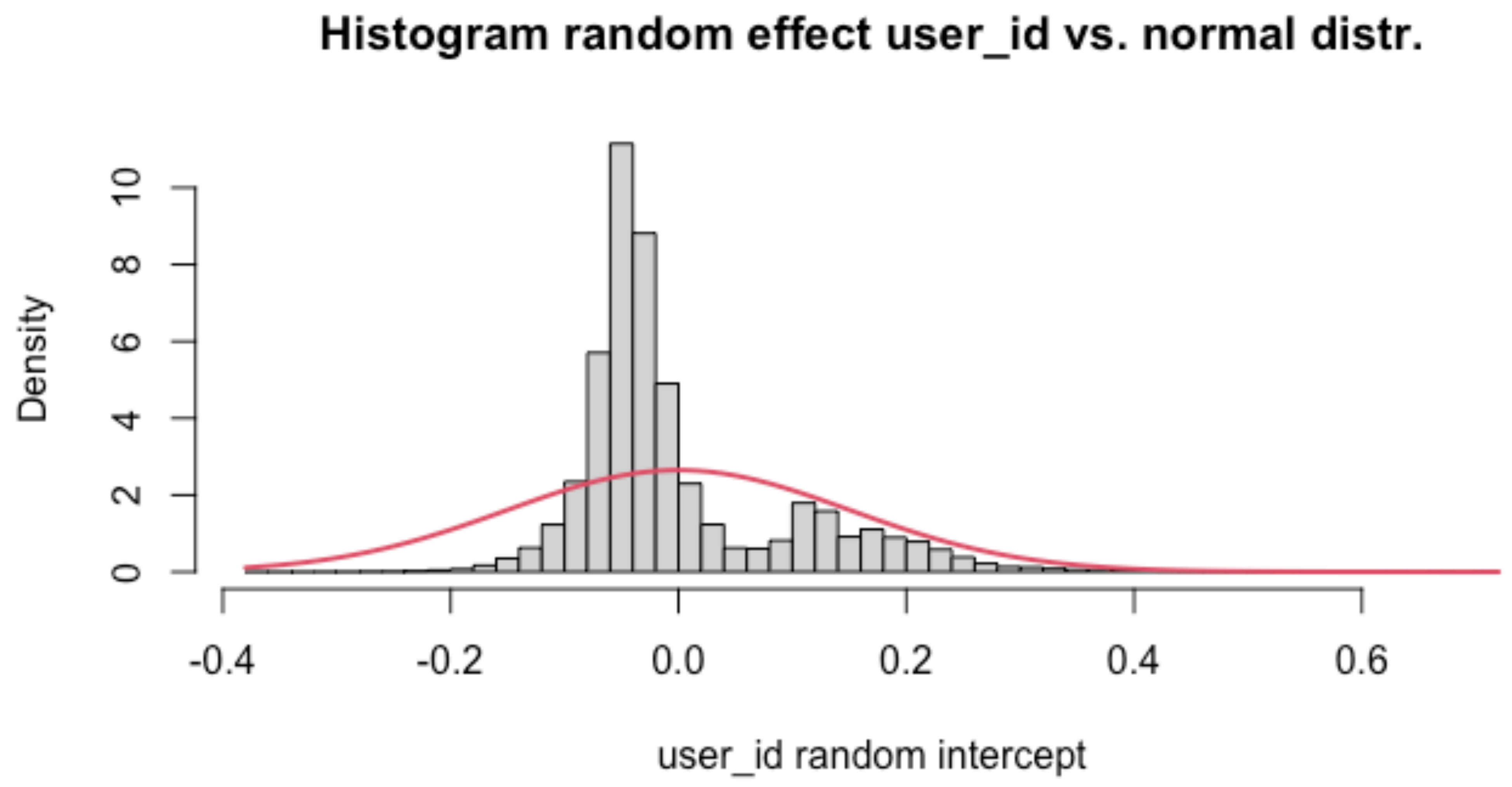
- Random effects $\alpha \overset{iid}{\sim} N(0,\ \sigma_\alpha^2 I)$, residual errors $\epsilon \overset{iid}{\sim} N(0,\ \sigma^2 I)$



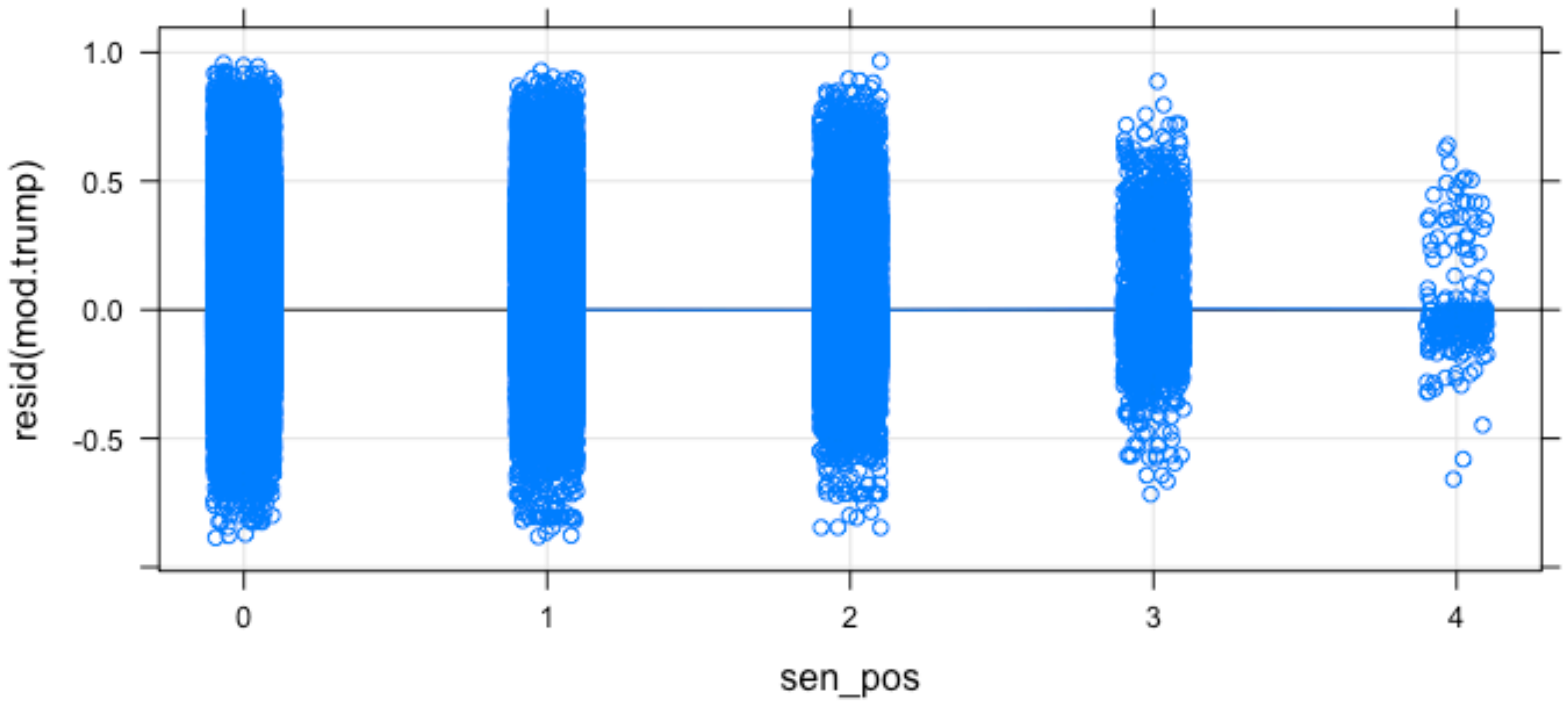


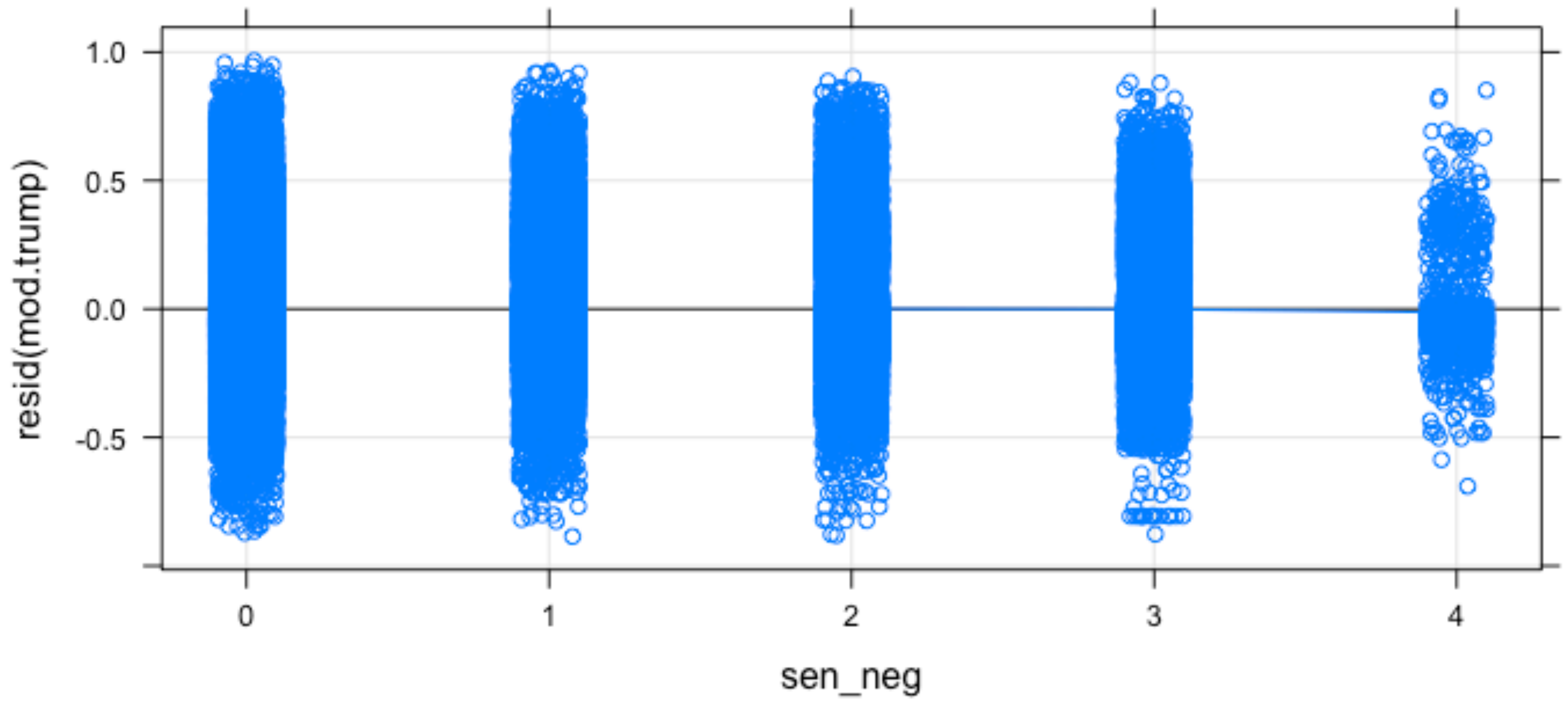
Insight #3.2: Linear Mixed Model use questionable





- Further indices of heteroscedasticity (non-constant variance)





Insight #3.2: Linear Mixed Model use questionable

- Single term deletions and model comparisons with different criteria (AIC, BIC) consistently select best model (in terms of goodness of fit and simplicity) as

Model: `retweets_reciprocal ~ followers + (1|user_id)`

- `followers` by far the covariate with largest explanatory power
- Questionable importance of `sen_pos` and `sen_neg`: significant by formal test, but in terms of explanatory model power?

Insight #3.2: Alternative models

- Original model by authors

Covariates	Significant at 95%
`Intercept`	**Yes**
`sen_pos`	No
`sen_neg`	**Yes**
`sen_pos:sen_neg`	No
`followers`	**Yes**

- "Best" normalizing transform of retweets + nominal factors + LMM

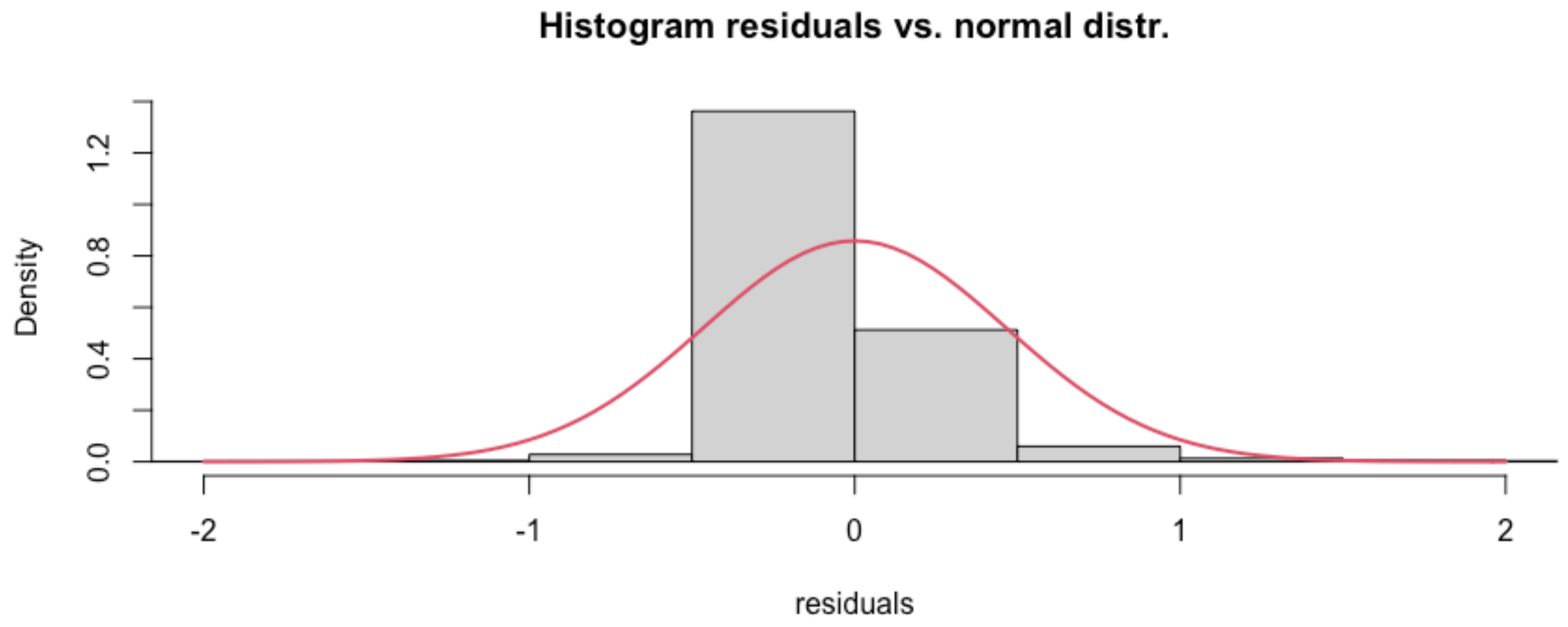
Covariates	Significant at 95%
`Intercept`	**Yes**
`sen_pos`	**Yes**
`sen_neg`	**Yes**
`sen_pos:sen_neg`	**Yes**
`followers`	**Yes**

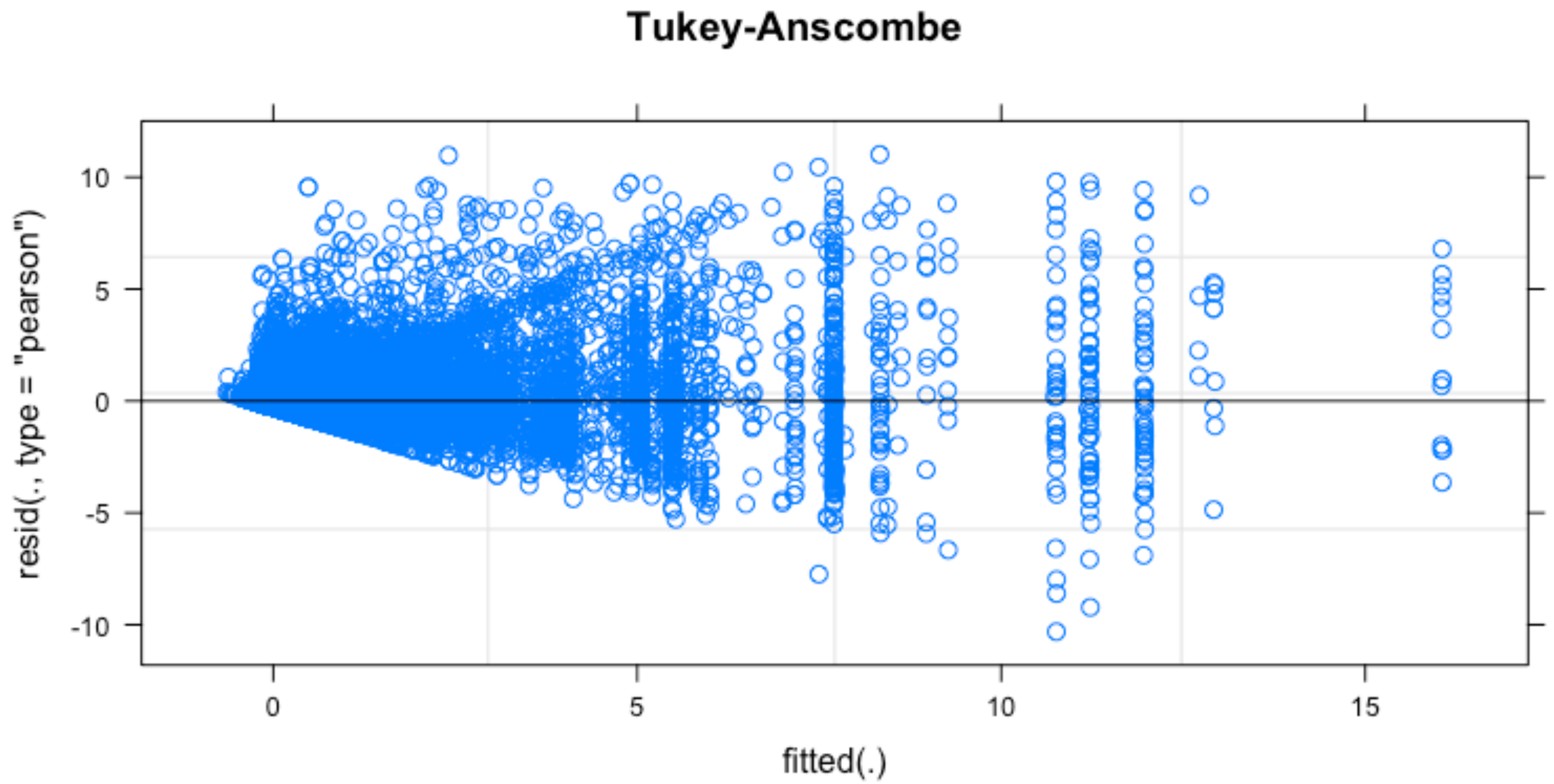
- GLMM + zero-inflated negative binomial family + nominal factors

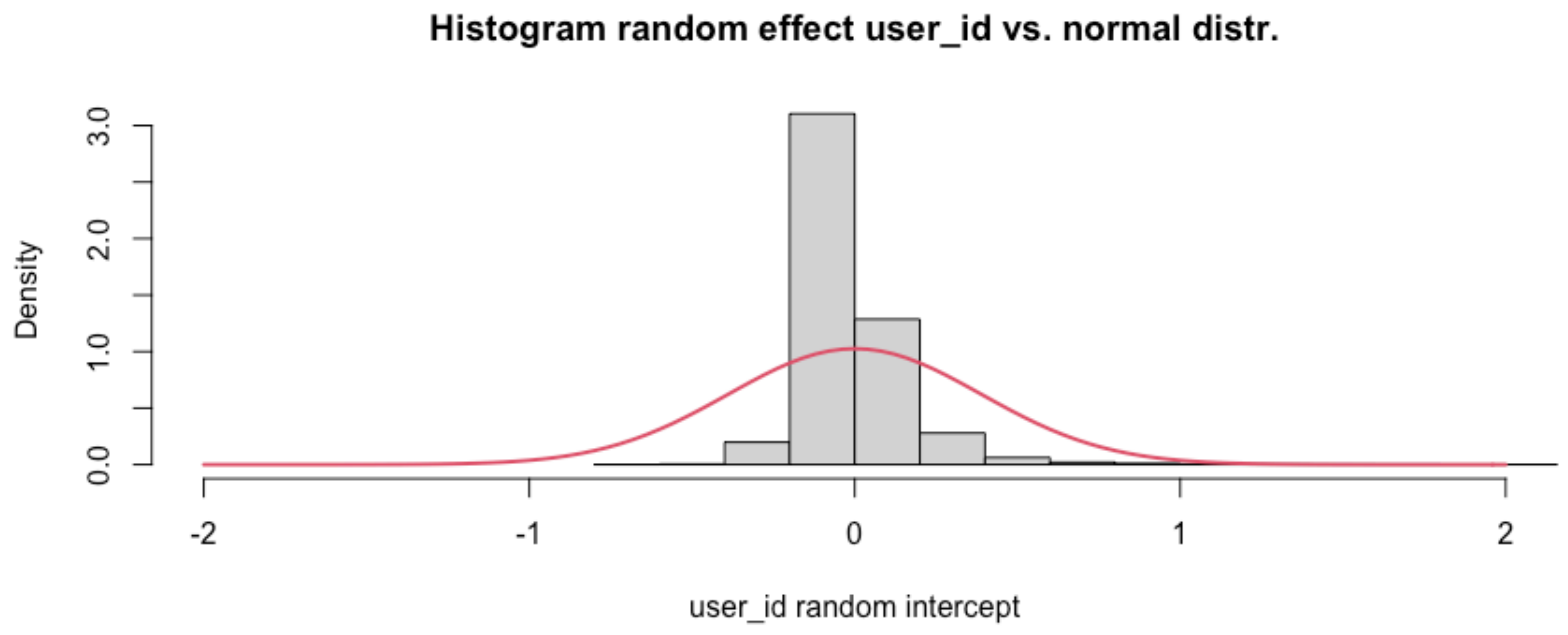
Covariates	Significant at 95%
`Intercept`	**Yes**
`sen_pos`	**Yes**
`sen_neg`	**Yes**
`sen_pos:sen_neg`	**Yes**
`followers`	**Yes**

Insight #3.2: Alternative models

- "Best" normalizing transform of retweets + nominal factors + LMM







- More possible alternative models: non-linear mixed effect models, gamma distribution family, other zero-inflated models

Insight #3.2: Summary

Linear Mixed Model fitted by authors:

- contains a coding error
- seems to violate model assumptions
- lacks proper transformation of covariates (factors)
- returns different results of significance compared to alternative models
- is potentially misspecified in assuming a linear relationship (see Annex)
- **should be analysed in more detail from a statistical viewpoint**

Insight #4: Political affiliation

3. Political affiliation of users (for Trump tweets)

- Classifying users as "Rep" or "Dem" based on simple heuristic
- (Try to) show that results from **2.** are due to intra-group and not inter-group dynamics

- True sample sizes smaller than claimed in paper
- Small samples in general: for Trump tweets 11% of data, for same-sex tweets only 0.49%!

Bail et al. (2018) public figure list (~4200):

- unbalanced (Conservatives ~1600 vs. Liberals ~2600)
- assigns people a score on a Conservative/Liberal **spectrum**, not Dem/Rep partisan label
- Claims for intra-group vs. inter-group dynamic doubtful because we cannot properly disentangle political views from party membership

Insight #4: Political affiliation

- Assignment rule $max(\#Rep, \#Dem)$ very simplistic

Examples:

- John follows 1000 people, 100 Rep, 50 Dem
- Jane follows 100 people, 51 Rep, 49 Dem
- Josh follows 100 people, 70 Rep, 30 Dem

Paper	Ours
Rep (?)	`> polit_aff(1000, 100, 50)` `[1] "Neu"`
Rep (?)	`> polit_aff(100, 51, 49)` `[1] "Neu"`
Rep	`> polit_aff(100, 70, 30)` `[1] "Con"`

- Better rule incorporates given thresholds, e.g. $\frac{\#Rep}{\#Dem} > 1.2, \quad \frac{\#Rep + \#Dem}{\#followers} > 0.2$

Insight #5: Implementation of text analysis

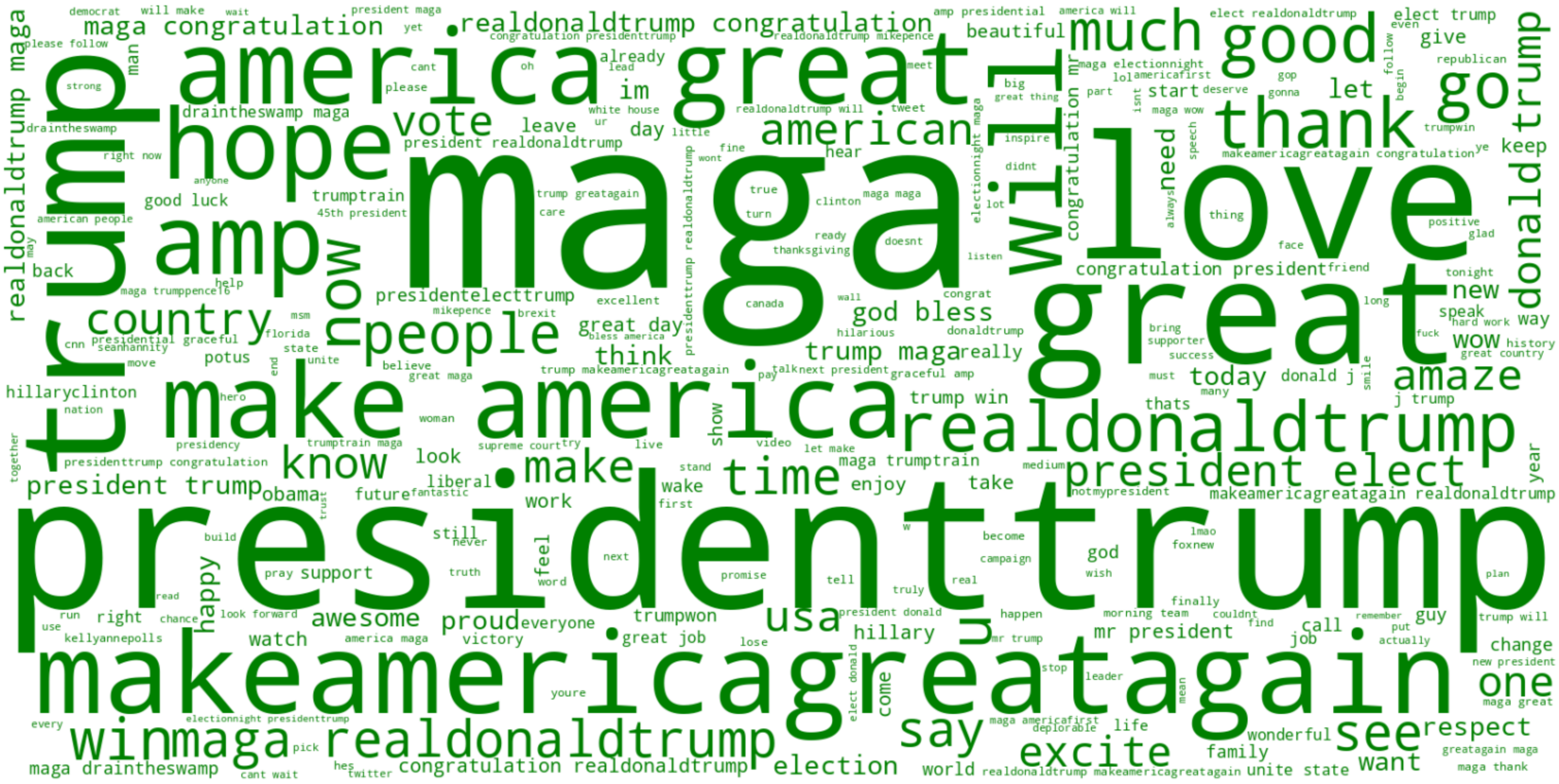
- Topic model pre-processing includes assigning tweets a label (Pos/Neg/Neu) based on valence score (`sen_pos + sen_neg`)

sen_pos	sen_neg	followers	valence	tweet_body
5	-5	563	0	THANK YOU SCOTUS Totally crying over here What an incredible day in our hist...
5	-5	875	0	Wooooohoooooo LoveWins Im in tears This Id absolutely AMAZING lt3 lt3 lt3 lt...
5	-5	9887	0	Im crying tears of joy Pure bliss LoveWins
5	-5	458	0	I WANNA CRY TEARS OF FUCKING JOY MEMBERS OF THE LBGT COMMUNITY YOU...
5	-5	34	0	THIS YES ME I literally keep finding more and more reasons to cry tears of utter...
5	-5	60	0	HOLY SHIT GAY MARRIAGE IS LEGAL IM SO FUCKING EXCITED I WAS CRYING TEA...
5	-5	5887	0	Im crying I cant believe this Obama sang Amazing Grace Charleston LoveWins p2
5	-5	2315	0	Ive watched the marriage equality snapchat 4 times now and I cant stop crying ...
5	-5	15	0	W O W Okay so Im literally crying tears of joy This is so fucking great SAME SEX...
5	-5	201	0	Im SO overjoyed Tears tears everywhere LoveWins

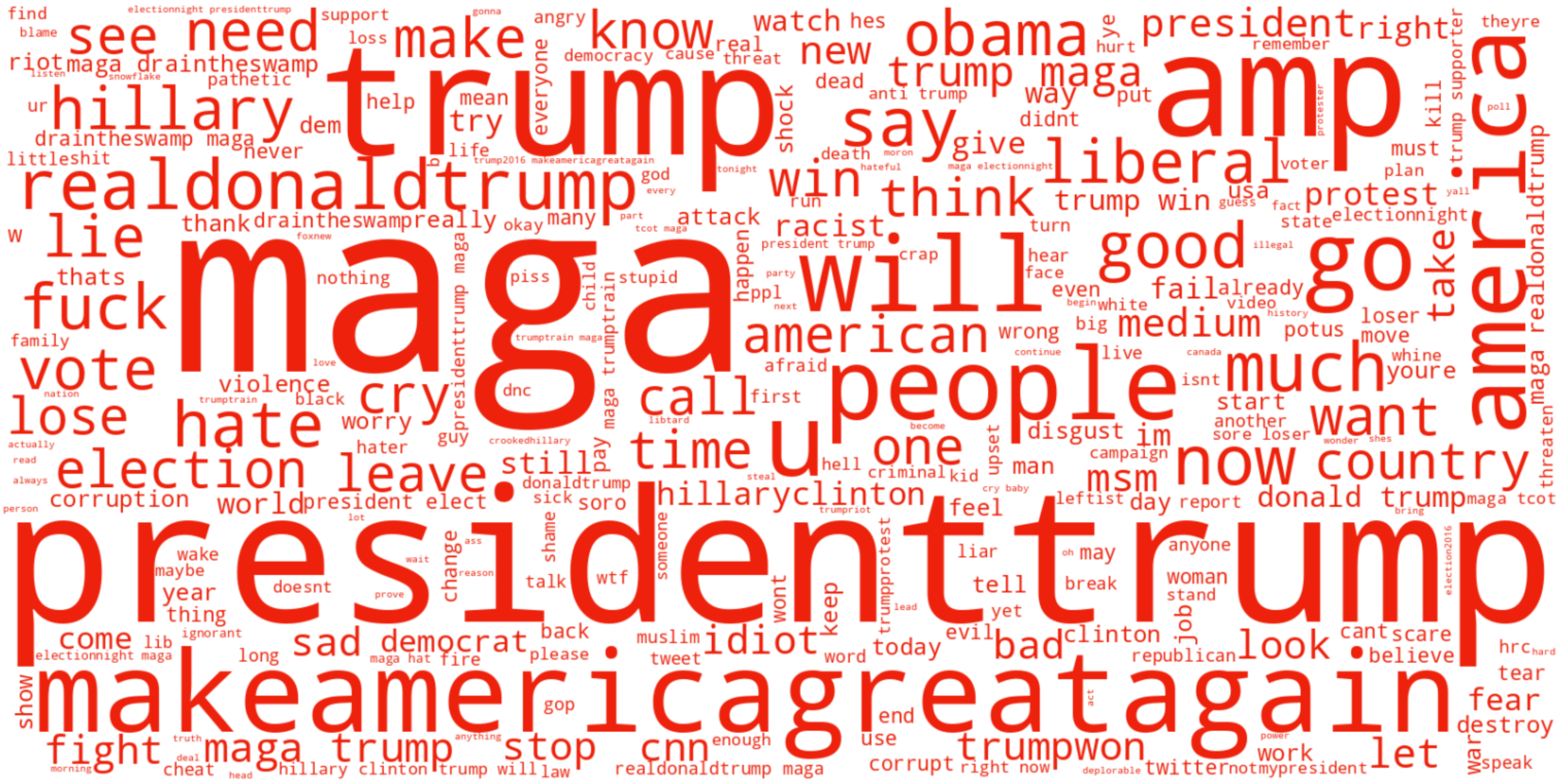
Emotionally neutral?

- Then data labelled "Neu" is removed - loss of over 2/3 of (expressive) data…
- Further analysis of topic modelling/LDA approach could reveal more issues

Insight #5: Implementation of text analysis



Insight #5: Implementation of text analysis



Insights: Summary

- Paper's analysis incomplete and/or lacking some scientific rigour
- Need for more factual evidence to back up various claims
- Need for a more self-critical assessment of proposed approaches and methods
- Potentially reconsider use of some methods, e.g. SentiStrength or classical LMM, and improve dataset quality
- Our analysis is by no means comprehensive, but raises some questions

Thank you for your attention!

Alexander Timans & Samuel Anzalone

10. December 2021

References (papers)

Papers

- Thelwall, Mike, et al. "Sentiment strength detection in short informal text." *Journal of the American society for information science and technology* 61.12 (2010): 2544-2558.
- Thelwall, Mike. Heart and soul: Sentiment strength detection in the social web with sentistrength, 2017. *Cyberemotions: Collective emotions in cyberspace*, 2014.
- Ribeiro, Filipe N., et al. "Sentibench-a benchmark comparison of state-of-the-practice sentiment analysis methods." *EPJ Data Science* 5.1 (2016): 1-29.
- Zimbra, David, Manoochehr Ghiassi, and Sean Lee. "Brand-related Twitter sentiment analysis using feature engineering and the dynamic architecture for artificial neural networks." *2016 49th Hawaii international conference on system sciences (HICSS)*. IEEE, 2016.
- Hutto, Clayton, and Eric Gilbert. "Vader: A parsimonious rule-based model for sentiment analysis of social media text." *Proceedings of the International AAAI Conference on Web and Social Media*. Vol. 8. No. 1. 2014.
- Bail, Christopher A., et al. "Supplementary Materials for “Exposure to Opposing Views can Increase Political Polarization: Evidence from a Large-scale Field Experiment on Social Media”."

References (complete)

Papers

- Thelwall, Mike, et al. "Sentiment strength detection in short informal text." *Journal of the American society for information science and technology* 61.12 (2010): 2544-2558.
- Thelwall, Mike. Heart and soul: Sentiment strength detection in the social web with sentistrength, 2017. *Cyberemotions: Collective emotions in cyberspace*, 2014.
- Ribeiro, Filipe N., et al. "Sentibench-a benchmark comparison of state-of-the-practice sentiment analysis methods." *EPJ Data Science* 5.1 (2016): 1-29.
- Zimbra, David, Manoochehr Ghiassi, and Sean Lee. "Brand-related Twitter sentiment analysis using feature engineering and the dynamic architecture for artificial neural networks." *2016 49th Hawaii international conference on system sciences (HICSS)*. IEEE, 2016.
- Hutto, Clayton, and Eric Gilbert. "Vader: A parsimonious rule-based model for sentiment analysis of social media text." *Proceedings of the International AAAI Conference on Web and Social Media*. Vol. 8. No. 1. 2014.
- Bail, Christopher A., et al. "Supplementary Materials for “Exposure to Opposing Views can Increase Political Polarization: Evidence from a Large-scale Field Experiment on Social Media”."

Resources

- https://data.library.virginia.edu/understanding-ordered-factors-in-a-linear-model/
- http://bbolker.github.io/mixedmodels-misc/glmmFAQ.html model-diagnostics
- https://stat.ethz.ch/~meier/teaching/anova/random-and-mixed-effects-models.html
- https://doi.org/10.1111/2041-210X.13434
- https://ethz.ch/content/dam/ethz/special-interest/math/statistics/sfs/Education/Advanced%20Studies%20in%20Applied%20Statistics/course-material-1921/Regression/MixedModels_Lab.pdf
- https://bookdown.org/animestina/phd_july_19/testing-the-assumptions.html
- https://www.tidytextmining.com/topicmodeling.html
- https://cran.r-project.org/web/packages/glmmTMB/vignettes/glmmTMB.pdf
- https://cran.r-project.org/web/packages/bestNormalize/vignettes/bestNormalize.html
- Color scheme: https://www.schemecolor.com/twitter-shades.php
- Science article: https://www.science.org/content/article/election-polling-trouble-can-internet-data-save-it

COLOR	INFORMATION
	Name: Blue Jeans Hex: #55ACEE RGB: (85, 172, 238) CMYK: 0.642, 0.277, 0, 0.066

Annex - Model comparison

```
> r.squaredGLMM(mod.trump); r.squaredGLMM(mod.trump.nofollow)
           R2m       R2c
[1,] 0.1131854 0.4122972
               R2m      R2c
[1,] 0.00004290774 0.408641
```

```
# Term deletions and model comparisons
m4 <- lmer(retweets_reciprocal ~ sen_pos + sen_neg
           + scale(followers_log) + (1|user_id), d.trump)
m3 <- lmer(retweets_reciprocal ~ sen_neg + scale(followers_log) + (1|user_id), d.trump)
m2 <- lmer(retweets_reciprocal ~ sen_pos + scale(followers_log) + (1|user_id), d.trump)
m1 <- lmer(retweets_reciprocal ~ scale(followers_log) + (1|user_id), d.trump)
m0 <- lmer(retweets_reciprocal ~ 1 + (1|user_id), d.trump)
```

- Anova: best model by AIC m3; best model by BIC m1
- MuMIn: best model by AICc m1
- performance: best model by AIC: m1; BIC: m1

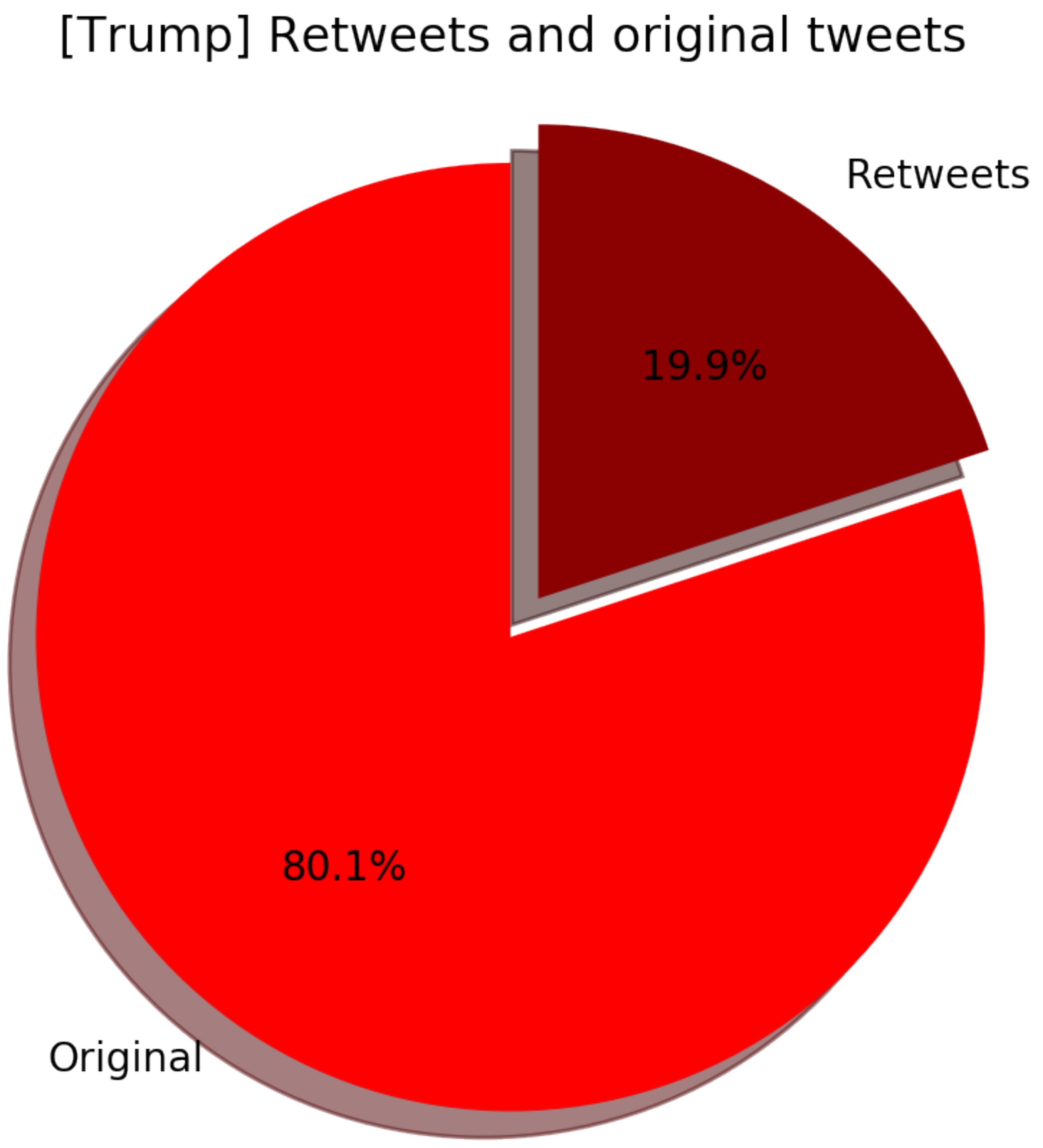
```
> MuMIn::model.sel(m0, m1, m2, m3, m4, mod.trump) #best model by AICc: m0
Model selection table
          (Int) scl(fll_log)    sen_pos  sen_neg sen_neg:sen_pos           family df    logLik   AICc    delta weight
m1       0.1489      0.09260                                      gaussian(identity)  4  2742.396 -5476.8     0.00  0.913
m3       0.1480      0.09262            0.001613                  gaussian(identity)  5  2741.038 -5472.1     4.72  0.086
m2       0.1491      0.09259 -0.0002412                           gaussian(identity)  5  2735.984 -5462.0    14.83  0.001
m4       0.1481      0.09261 -0.0001067 0.001607                  gaussian(identity)  6  2734.563 -5457.1    19.67  0.000
mod.trump 0.1479     0.09262  0.0002239 0.001951      -0.0005761 gaussian(identity)  7  2728.531 -5443.1    33.73  0.000
m0       0.1326                                                   gaussian(identity)  3 -4476.653  8959.3 14436.10  0.000
Models ranked by AICc(x)
Random terms (all models):
‘1 | user_id’
```

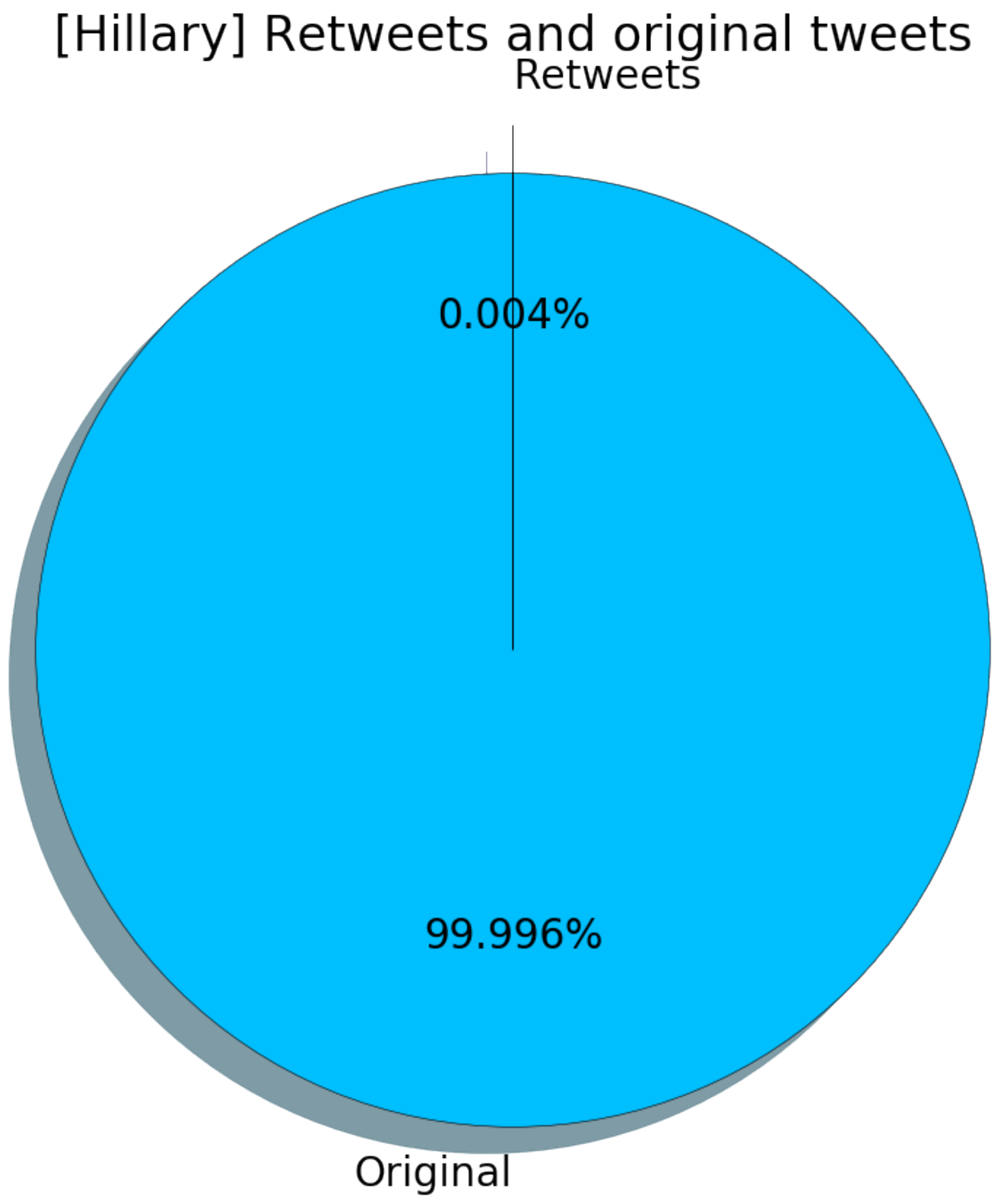
```
> performance::compare_performance(m0, m1, m2, m3, m4, mod.trump) # long run time
# Comparison of Model Performance Indices

Name      |           Model |       AIC | AIC weights |       BIC | BIC weights | R2 (cond.) | R2 (marg.) |   ICC |  RMSE | Sigma
-----------------------------------------------------------------------------------------------------------------------------------
m0        | lmerModLmerTest |  8959.306 |     < 0.001 |  8990.914 |     < 0.001 |      0.409 |      0.000 | 0.409 | 0.188 | 0.210
m1        | lmerModLmerTest | -5476.792 |       0.913 | -5434.648 |       1.000 |      0.412 |      0.113 | 0.337 | 0.192 | 0.211
m2        | lmerModLmerTest | -5461.967 |     < 0.001 | -5409.287 |     < 0.001 |      0.412 |      0.113 | 0.337 | 0.192 | 0.211
m3        | lmerModLmerTest | -5472.075 |       0.086 | -5419.395 |     < 0.001 |      0.412 |      0.113 | 0.337 | 0.192 | 0.211
m4        | lmerModLmerTest | -5457.126 |     < 0.001 | -5393.910 |     < 0.001 |      0.412 |      0.113 | 0.337 | 0.192 | 0.211
mod.trump | lmerModLmerTest | -5443.062 |     < 0.001 | -5369.309 |     < 0.001 |      0.412 |      0.113 | 0.337 | 0.192 | 0.211
```

Annex - Insight #1: Quality of dataset – Original tweets

- 20% of the tweets in the Trump dataset are retweets
- ~0% of the tweets in the Hillary dataset are retweets





Annex - Insight #2: SentiStrength

Valence = sen_pos + sen_neg

Fuckin priceless MAGA ImWithHer NotMyPresident https tco BrTiMdbb76	fuckin priceless …	4
Oh fucking great the lists have begun Hello Fascism PresidentTrump https tco qZdKWN32xP	oh fuck great the …	4
I wish I was there to sell tissue Id make my money last night Lol cucks MAGA Priceless loversoflies h…	i wish i be there t…	4
The moment you realize that You just shit your career down the toilet for HillaryClinton Priceless htt…	the moment you r…	4

Issues identifying "crying" in positive context

sen_pos	sen_neg	followers	valence	tweet_body
5	-5	563	0	THANK YOU SCOTUS Totally crying over here What an incredible day in our hist…
5	-5	875	0	Wooooohoooooo LoveWins Im in tears This Id absolutely AMAZING lt3 lt3 lt3 lt…
5	-5	9887	0	Im crying tears of joy Pure bliss LoveWins
5	-5	458	0	I WANNA CRY TEARS OF FUCKING JOY MEMBERS OF THE LBGT COMMUNITY YOU…
5	-5	34	0	THIS YES ME I literally keep finding more and more reasons to cry tears of utter…
5	-5	60	0	HOLY SHIT GAY MARRIAGE IS LEGAL IM SO FUCKING EXCITED I WAS CRYING TEA…
5	-5	5887	0	Im crying I cant believe this Obama sang Amazing Grace Charleston LoveWins p2
5	-5	2315	0	Ive watched the marriage equality snapchat 4 times now and I cant stop crying …
5	-5	15	0	W O W Okay so Im literally crying tears of joy This is so fucking great SAME SEX…
5	-5	201	0	Im SO overjoyed Tears tears everywhere LoveWins

Annex - Insight #2: SentiStrength

- Potential improvement: use different sentiment analysis tool, preferably ML based
- SentiStrength vs. VADER (rescaled) on 10 000 samples

```
> cor(valence.vader, valence.senti)
[1] 0.5489618
```

tweet	tweet_lemma	vader	sentistrength
GREAT CHOICE KT Mcfarland Tabbed as Deputy National Security Adviser ma4trump MAGA massGOP masspoli https tco 4IKDjd5CSM	great choice kt m…	4	-4
CNN owes Hilary a big apology for misleading her with clearly non existent win polls PresidentTrump USElection2016	cnn owe hilary a …	4	-3
HamiltonMusical BrandonVDixon you Just helped Trump pence win another 4 years bravo Way to divide us great job Gear message maga	hamiltonmusical …	4	-3
CassandraMarieW This isnt devastating This is exciting This is the beginning of Making America Great Again MAGA	cassandramariew …	4	-3
I am praying that SheriffClarke is put in charge of Homeland Security Hes like Clint Eastwood amp Chuck Norris rolled into one badass maga	i be pray that she…	4	-3
Wow only in America Border Crossing Transgender Person Freezes Eggs In Hopes Of Being Dad Someday maga https tco ermYOPJhbZ	wow only in amer…	4	-3
Trump win is no catastrophe its politics Stephen Cohen https tco MKlF3fAF0z tcot ccot gop maga polusa	trump win be no …	4	-3
Some people worried about their life Im here like God please let realDonaldTrump win MakeAmericaGreatAgain atleasthehonest	some people worr…	4	-2

tweet	tweet_lemma	vader	sentistrength
Its amazing how a bunch of fucking idiots can fuck things up so much in 1 night of voting PresidentTrump	its amaze how a …	-3	3
georgesoros is a scumbag hate monger who needs to be called out for the fraud that he is Chickenhawk SMH https tco TX0x6YpklO	georgesoros be a…	-3	2
SamuelLJackson its time to expatriate dumb ass dont be a liar as well calexit presidenttrump	samuelljackson it…	-3	2
LeoDiCaprio Hey Leonard Just want to pass along a quick Fuck You for hating on Trump Say bye to Americas war on climate Thanks MAGA	leodicaprio hey le…	-3	2
MikePence getting booed at hamiltonmusical is just more proof what pathetic sore losers Crooked Hillary supporte https tco Rv9ujBHbEY	mikepence get bo…	-3	2
Dems and Libs can try to blame whatever isms they want This vote shows that the American people reject their failure PresidentTrump	dems and libs ca…	-3	2
Is PresidentTrump death of democracy Not yet voters used system to give message of dissatisfaction amp pain elite reactions now the key	be presidenttrum…	-3	2

Annex - Insight #2: SentiStrength

- From original paper by Thelwall et al. (2010):
- SentiStrength partially outperformed by SVM

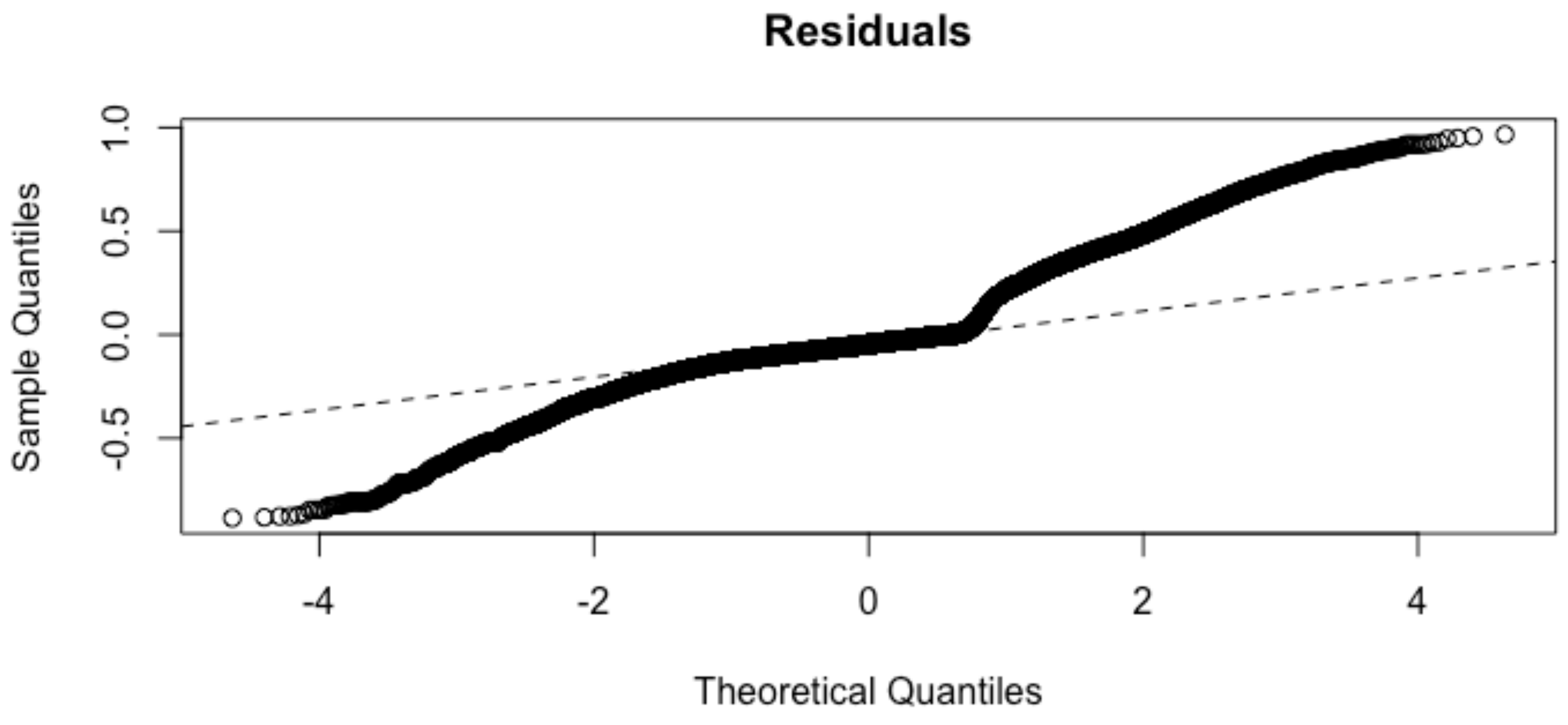
set. Overall, it seems that SentiStrength is not good at identifying negative emotion, but that this is a hard task for the short texts analyzed here. Note also that the mean percentage absolute error for the random category is over 100% due to the predominance of 1: as the correct category for negative sentiment.

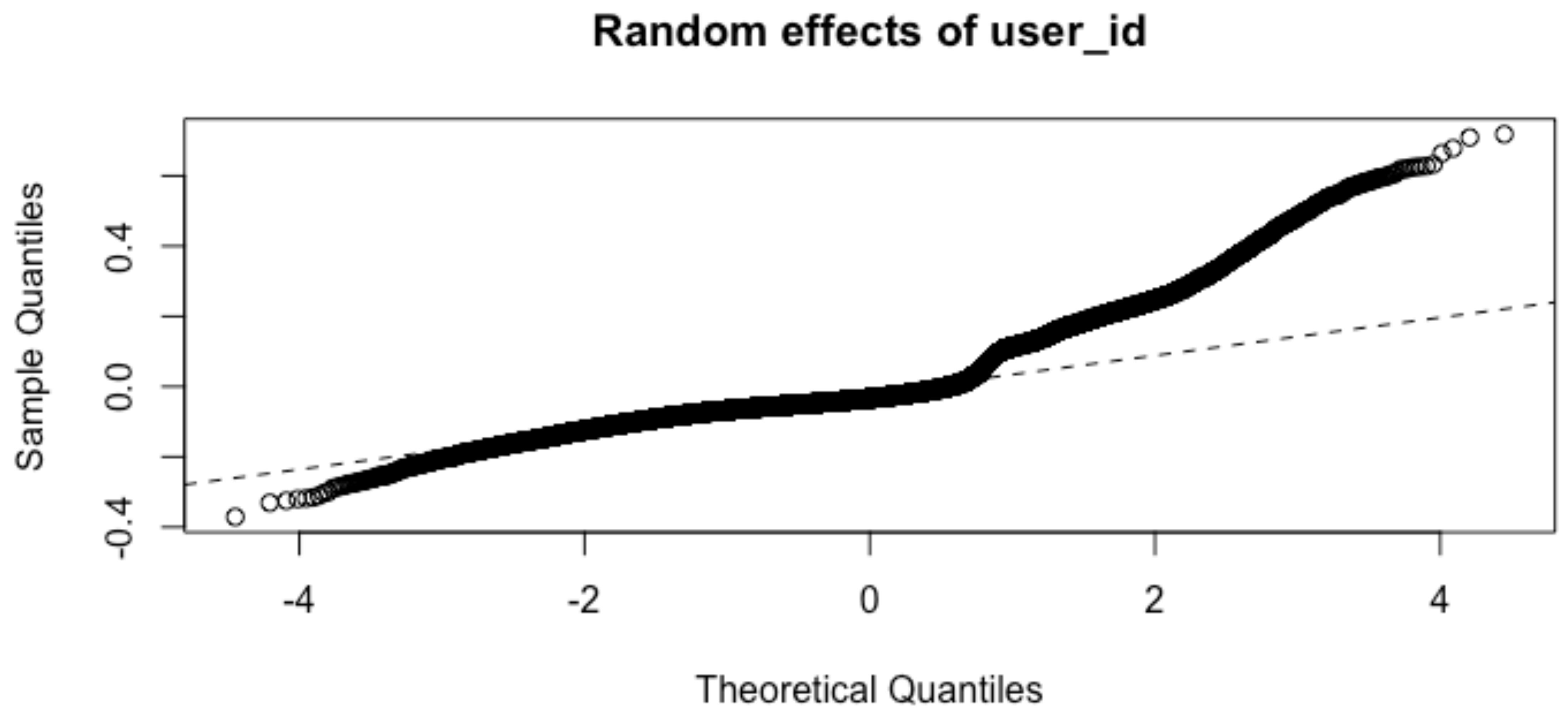
The remainder of this article focuses on positive sentiment alone; the results for negative sentiment are not significant.

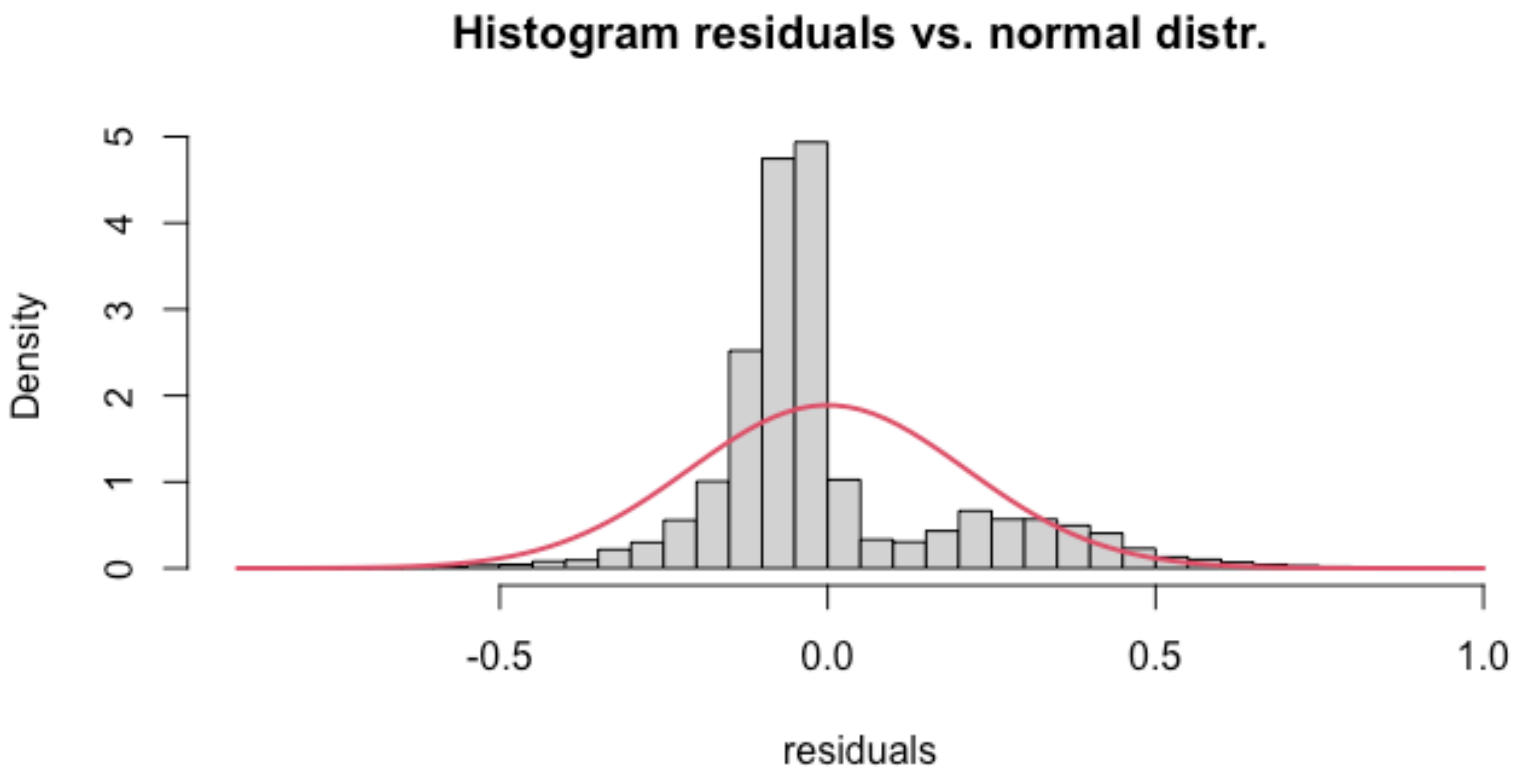
- From a later paper by Thelwall (2017):
- SentiStrength is outperformed on Twitter data by "Best machine learning" for positive (60.7% vs. 56.3%) and negative (64.3% vs. 61.7%) emotion accuracy and also has lower correlations with human-coded scores (~2% difference)

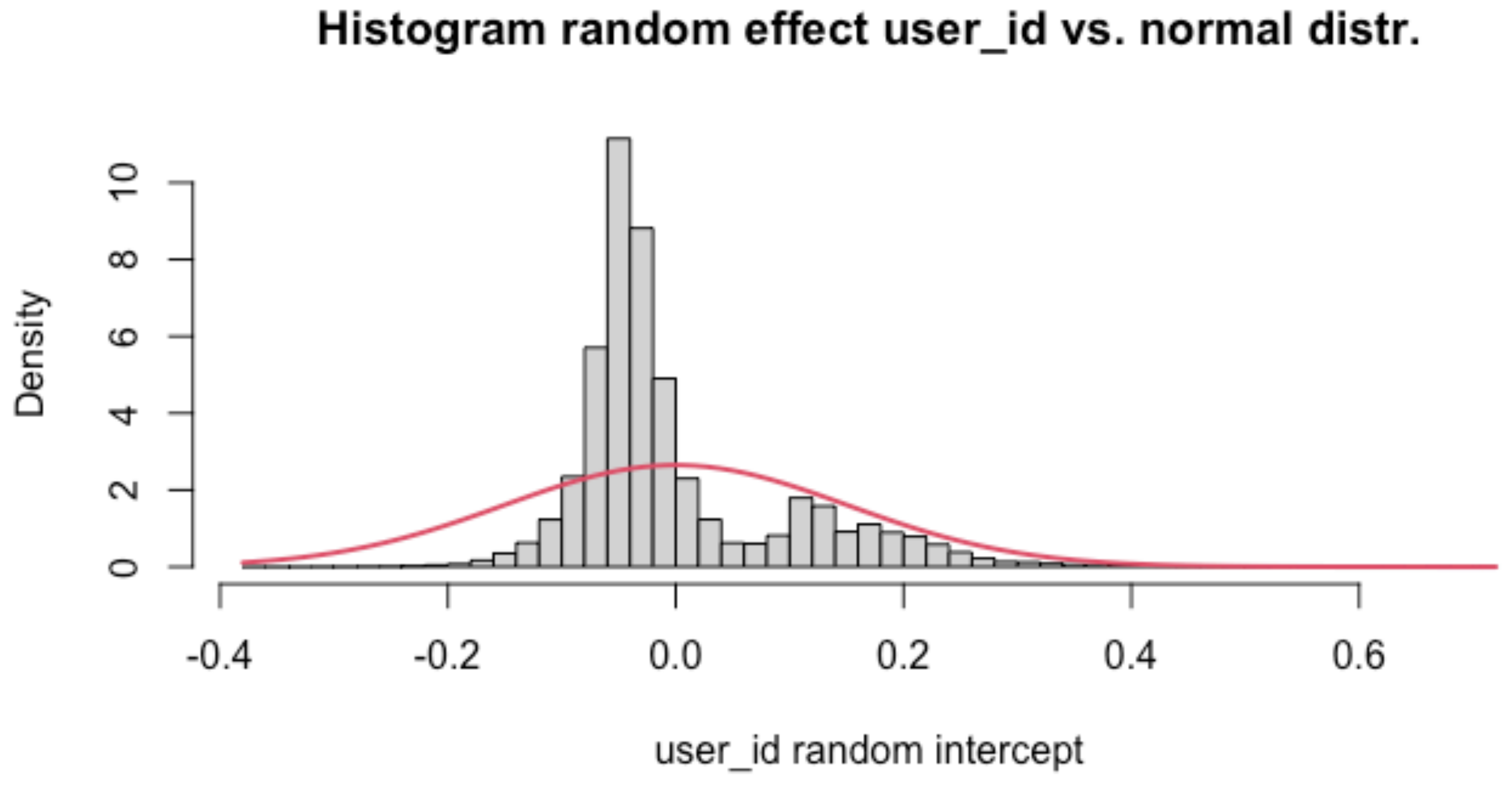
Twitter		
Unsupervised SentiStrength	59.2%	66.1%
Supervised SentiStrength	63.7%	67.8%
Best machine learning	**70.7%**	**75.4%**

Annex - Insight #3.2: Linear Mixed Model use questionable









Annex - Insight #3.2: Alternative models

Alternative models tested:

- Retweets on original scale + LMM
- Encode `sen_pos` and `sen_neg` as factors (nominal/ordinal) + LMM
- "Best" normalizing transform of retweets (sqrt) + nominal factor encoding + LMM
- GLMM + zero-inflated negative binomial family + nominal factor encoding

Annex - Insight #3.2: Alternative models

- Encode `sen_pos` and `sen_neg` as **ordinal** factors + LMM
- Probably most accurately reflects true nature of variable
- Polynomially encoded factors capture trends in the data -> non-linear trends significant, while linear are not?

```
Fixed effects:
                          Estimate   Std. Error          df t value              Pr(>|t|)
(Intercept)              0.1511414    0.0077458 226728.7742157  19.513 < 0.0000000000000002 ***
sen_pos.L                0.0073303    0.0233919 219352.3162983   0.313             0.753999
sen_pos.Q                0.0011111    0.0198987 220438.2861838   0.056             0.955469
sen_pos.C               -0.0113104    0.0137828 234459.8299327  -0.821             0.411863
sen_pos^4               -0.0121514    0.0077729 256431.5434221  -1.563             0.117980
sen_neg.L               -0.0028584    0.0216557 205383.7838294  -0.132             0.894991
sen_neg.Q               -0.0218545    0.0191253 211814.6196991  -1.143             0.253164
sen_neg.C               -0.0388795    0.0149178 247343.8342158  -2.606             0.009155 **
sen_neg^4               -0.0415953    0.0116359 269039.6369961  -3.575             0.000351 ***
scale(followers_log)     0.0926176    0.0007362 100793.3210579 125.803 < 0.0000000000000002 ***
sen_pos.L:sen_neg.L      0.0046961    0.0653306 198059.8196181   0.072             0.942696
sen_pos.Q:sen_neg.L     -0.0086811    0.0556229 199555.2610797  -0.156             0.875978
sen_pos.C:sen_neg.L     -0.0311721    0.0389049 220806.3107970  -0.801             0.422995
sen_pos^4:sen_neg.L     -0.0254775    0.0223965 252870.7666640  -1.138             0.255303
sen_pos.L:sen_neg.Q     -0.0336328    0.0577688 205426.6841202  -0.582             0.560435
sen_pos.Q:sen_neg.Q     -0.0239800    0.0491636 206641.4877932  -0.488             0.625720
sen_pos.C:sen_neg.Q     -0.0171999    0.0343003 225694.4679531  -0.501             0.616055
sen_pos^4:sen_neg.Q     -0.0127360    0.0196302 254173.2879423  -0.649             0.516469
sen_pos.L:sen_neg.C     -0.0944231    0.0454454 245692.7105522  -2.078             0.037736 *
sen_pos.Q:sen_neg.C     -0.0510643    0.0385976 246007.0926221  -1.323             0.185839
sen_pos.C:sen_neg.C     -0.0178670    0.0263056 251230.9140604  -0.679             0.497005
sen_pos^4:sen_neg.C     -0.0053309    0.0143538 260856.8507419  -0.371             0.710343
sen_pos.L:sen_neg^4     -0.1222412    0.0356097 269265.7847315  -3.433             0.000597 ***
sen_pos.Q:sen_neg^4     -0.0905306    0.0301985 269254.0207713  -2.998             0.002719 **
sen_pos.C:sen_neg^4     -0.0367088    0.0203386 268401.4109000  -1.805             0.071094 .
sen_pos^4:sen_neg^4     -0.0069021    0.0107227 267818.1148863  -0.644             0.519775
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
```

Annex - Insight #4: Political affiliation

3. Political affiliation of users (for Trump tweets)

- Classifying users as "Rep" or "Dem" based on simple heuristic
- (Try to) show that results from **2.** are due to intra-group and not inter-group dynamics

- Numbers don’t add up?

hashtags that celebrated Trump’s victory, we tested a subsample of posts (30,830 tweets), that were

negative (minimum 2 on a scale to 4 in negative intensity), and had at least one retweet. We

```
> nrow(d.trump[(d.trump$retweets >= 1 & d.trump$sen_neg >= 2), ]) #11932, not 30830 ?
[1] 11932
```

- Small samples: for Trump tweets 11% of data, for same-sex tweets only 0.49%!

Bail et al. (2018) public figure list:

- unbalanced and has its own issues

Despite these steps, pilot analyses of the ideological continuum consistently identified a small number of elected officials who were misclassified according to our measure. Each of these individuals were very high profile opinion leaders such as Mitch McConnell and John McCain, who have very large followings that include a large number of non-Republicans, which made them centrists instead of conservatives in our original

- assigns people a score on a Conservative/Liberal **spectrum**, not Dem/Rep partisan label
- Claims for intra-group vs. inter-group dynamic doubtful because we cannot properly disentangle political views from party membership

Speaking parts (to be removed)

- Slide 1-7: Samuel, 5m
- Slide 8-16: Alex, 7-8m
- Slide 17-28: Samuel, 7-8m
- Slide 29-40: Alex, 7-8m
- Slide 41-44: Samuel, 3-4m