Elon Musk Makes Twitter 😔🤬😭!

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Title

Motivation

Our team shared a **fascination** with Elon Musk's power, not only as a CEO and millionaire, but as an "influencer" on Twitter.

We had been **following** Elon Musk's Twitter acquisition process since it was gaining a lot of attention.

We believe he has a **special role** as an influential figure.

We wanted to **test** this idea.

Human-Centered Argument

Why and how can a single person, in this case Elon Musk, have so much influential power?

These are usually questions we ask about/in **political settings**.

About presidents, prime ministers, royal families, etc.

But powerful figures are now on the internet, **not just in government**.

They have a **significant impact** (shifting the stock market, attracting retweets, etc.)

Elon Musk seems to have a **special role**, but does he really?

Research Question / Thesis

Research Question: To what extent has Elon Musk's takeover of Twitter affected how users emotionally respond to his content on Twitter?

Thesis: Elon Musk's takeover of Twitter affected how users emotionally respond to his content on Twitter by:

Argument 1: [VADER] Shifting the sentiment of responses to his tweets towards being more negative.

Argument 2: [NRCLex] Intensifying feelings of "sadness", "anger", and "fear" while dissipating feelings of "trust".

Argument 3: [Statistics] After the takeover users feel more passionate about Elon Musk's content, and interact with it more often.

Methodology

- **Twitter API**
  - Emulate features tracked by other publicly available datasets.
  - Range: 26 August-18 November 2022 (Musk's Takeover Occurs ~ 1 November)
- **Tools**
  - Twitter Developer Account
  - Tweepy (Python Library)
  - TwitterAPI (Python Library)
  - VADER and NRCLex (refer to Slide 10)

Kaggle DataSet Features

(Ready-Made)

Elon Musk Tweets (2010 - 2022)

Data   Code (4)   Discussion (3)

Column Descriptions:

`#:` Index.
`id:` ID of tweet.
`conversation_id:` : ID of twitter conversation/thread.
`created_at:` Unknown, some kind of time/location index from twitter. (?)
`date:` Date of Creation.
`timezone:` Timezone.
`place:` Location.
`tweet:` Contents of tweet, tweet body.
`language:` Language of tweet.
`hashtags:` Hashtags in the tweet "#".
`cashtags:` Cashtags in the tweet "$", often used for stock tweets.
`user_id:` ID of the tweet/reply author.
`user_id_str:` User ID but in string format.
`username:` Username of the tweet/reply author.
`name:` Name of tweet/reply author.
`day:` Day of the week in which the tweet was published.
`hour:` Hour of the day in which the tweet was published.

Key Principles

- **Audience:** Who is affected by the system?

	tweet_id	screen_name	text	timestamp	conversation_id
0	1593551192176500736	elonmusk	@lionxmah @folha ?	2	1590384919829962752
1	1593541440671338496	elonmusk	@AOC You're welcome	2022-11-18 09:47:40+00:00	1593399168764190720
2	1593535742285750272	elonmusk	@WholeMarsBlog Record numbers of users are log...	2022-11-18 09:25:02+00:00	1593315850546618368
3	1593528527873200130	elonmusk	@piersmorgan Seriously	2022-11-18 08:56:22+00:00	1593521238915403776
4	1593494261038649344	elonmusk	https://t.co/JU073T756X	2022-11-18 06:40:12+00:00	1593494261038649344
...	...	...	...	...	...
3194	1509474644306411522	elonmusk	@teslaownersSV @PPathole @SpaceX Will take of it	2022-03-31 10:16:14+00:00	1508967431548506112
3195	1509416977449857029	elonmusk	@teslaownersSV @SpaceX You may be in an area t...	2022-03-31 06:27:05+00:00	1508967431548506112
3196	1509308717094916101	elonmusk	@BillyM2k 🤣	2022-03-30 23:16:54+00:00	1509304553811841027
3197	1509087321685209088	elonmusk	@JohnnaCrider1 Ok	2022-03-30 08:37:09+00:00	1508488978965614593
3198	1509078170200383492	elonmusk	@harsimranbansal Canada requires charging by t...	2022-03-30 08:00:47+00:00	1508780025264455685

3199 rows × 5 columns

Tweepy

-> Gateway to user replies
-> Key to Elon Musk's textual interactions

-> Access to the tweet related stats
-> the number of likes, retweets, and followers

Data and Approach

(Custom-Made)

	tweet_id	screen_name	text	timestamp	conversation_id	replies_info
0	1593551192176500736	elonmusk	@lionxmah @folha ?	2	1590384919829962752	<__main__.reply_c object at 0x7fa792395970>
1	1593541440671338496	elonmusk	@AOC You're welcome	2022-11-18 09:47:40+00:00	1593399168764190720	<__main__.reply_c object at 0x7fa78f50ba30>
2	1593535742285750272	elonmusk	@WholeMarsBlog Record numbers of users are log...	2022-11-18 09:25:02+00:00	1593315850546618368	<__main__.reply_c object at 0x7fa79217a8e0>
3	1593528527873200130	elonmusk	@piersmorgan Seriously	2022-11-18 08:56:22+00:00	1593521238915403776	<__main__.reply_c object at 0x7fa79217afa0>
4	1593494261038649344	elonmusk	https://t.co/JU073T756X	2022-11-18 06:40:12+00:00	1593494261038649344	<__main__.reply_c object at 0x7fa78f50bdc0>

Data and Approach

Objects: designed to store list of dictionaries more compactly while running API

n_replies (int) + list of

{'edit_history_tweet_ids': ['1598314656313053187'],
'created_at': '2022-12-01T13:54:43.000Z',
'author_id': '1529757080986468352',
'conversation_id': '1593399168764190720',
'text': "@elonmusk @AOC We are counting on you to release all the reports that falsely claimed this information. If you can do that you'll be number one and millions of people's eyes. Millions are counting on you please don't let us down. You do consider yourself American right ????",
'id': '1598314656313053187',
'in_reply_to_user_id': '44196397'}

_info	reply_count	reply_text	created_at	conversation_id_r	author_id	in_reply_to_user_id	id	edit_hist
ply_c ect at 970>	42	[@elonmusk @Havi_HighOne Then fire yourself!, ...	[2022-12-01T15:30:46.000Z, 2022-12-01T02:42:53...	[1590384919829962752, 1590384919829962752, 159...	[1126612002166587392, 1559857123504291840, 148...	[44196397, 44196397, 1481833905577598977, 1487...	[1598338825134252033, 1598145580043489280, 159...	[[15983388 [159814558(
ply_c ect at a30>	259	[@Kroq44 @AOC You're right. Are you working du...	[2022-12-01T18:24:58.000Z, 2022-12-01T17:56:30...	[1593399168764190720, 1593399168764190720, 159...	[1554252246397120512, 1367206203223400452, 152...	[1586018719523737600, 765691822710542336, 3524...	[1598382663215108096, 1598375500602347538, 159...	[[15983826 [159837550(
ply_c ect at 8e0>	14	[@AmoneyResists @elonmusk @WholeMarsBlog Do yo...	[2022-11-29T23:13:32.000Z, 2022-11-29T22:02:15...	[1593315850546618368, 1593315850546618368, 159...	[827536285359288324, 137390049, 15189969664448...	[739844197935644672, 44196397, 44196397, 44196...	[1597730509106204672, 1597712571410567168, 159...	[[15977305 [15977125
ply_c ect at afa0>	13	[@piersmorgan @elonmusk They're not going to l...	[2022-12-01T14:05:15.000Z, 2022-12-01T14:04:10...	[1593521238915403776, 1593521238915403776, 159...	[1529757080986468352, 1529757080986468352, 829...	[216299334, 216299334, 216299334, 216299334, 2...	[1598317306119168003, 1598317033724301314, 159...	[[15983173 [15983170
ply_c ect at dc0>	63	[@AngelaBelcamino @elonmusk Looks like you try...	[2022-12-01T14:02:47.000Z, 2022-12-01T02:45:26...	[1593494261038649344, 1593494261038649344, 159...	[1356751399409876992, 1359707307182022660, 158...	[1685873604, 44196397, 1594306080309387265, 44...	[1598316684573642754, 1598146224183742464, 159...	[[15983166 [15981462

-> Unpacking the data as it is stored in the objects (eases analysis)
-> Splitting DataFrame to two sections (before and after takeover)

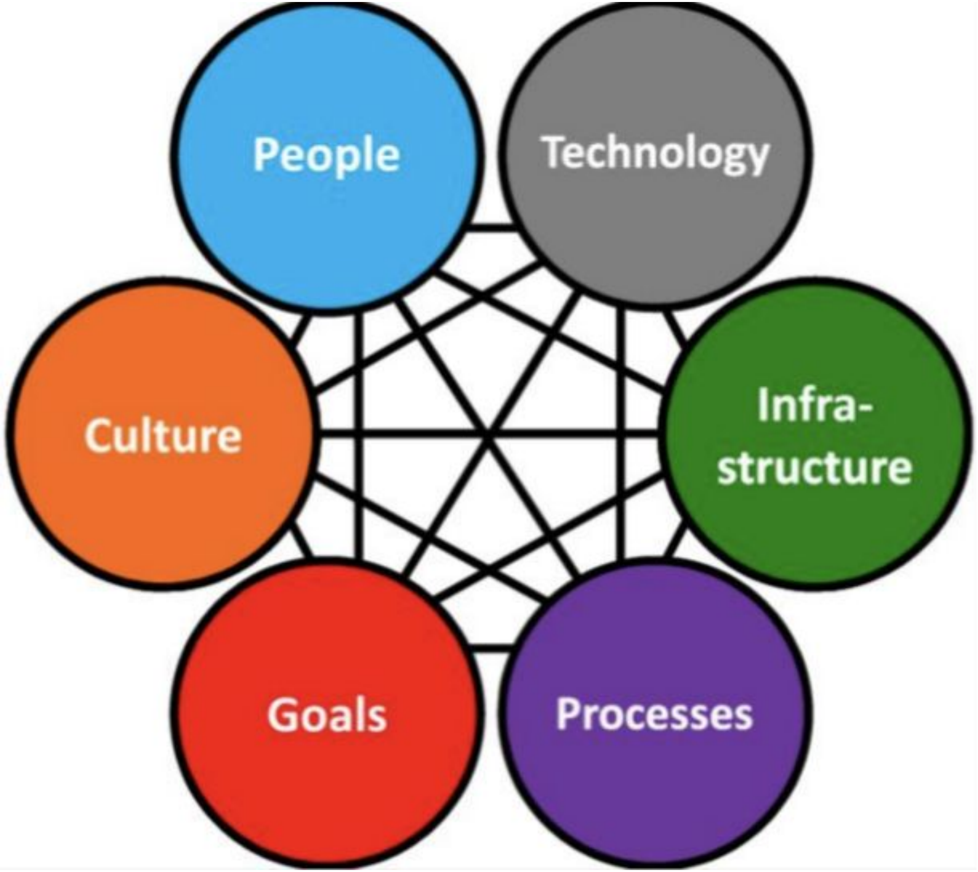
Data and Approach

VADER vs NRCLex

- **VADER (Valence Aware Dictionary and sEntiment Reasoner):**
    - VADER is effective at sentimentally deconstructing tweets as it has "been found to be especially useful in the analysis of short texts" (Schöne et al.)
    - Provides little analysis on psycho-emotional descriptors (binary classification)
- **NRCLex**
    - The NRCLex library can measure "the emotional effect from a body of text" (LZP).
    - The library is built using approximately 27,000 words and is based on the National Research Council Canada (NRC) affect lexicon and NLTK library's WordNet synonym sets" (LZP).

Tradeoff

Accuracy
vs
Depth



- Human behaviors are not static but they are emulated digitally on social platforms and are highly volatile
- Allows us to identify the dynamics between Twitter interactions (that are characterized by a leader-follower relationship) and the social environment it engenders

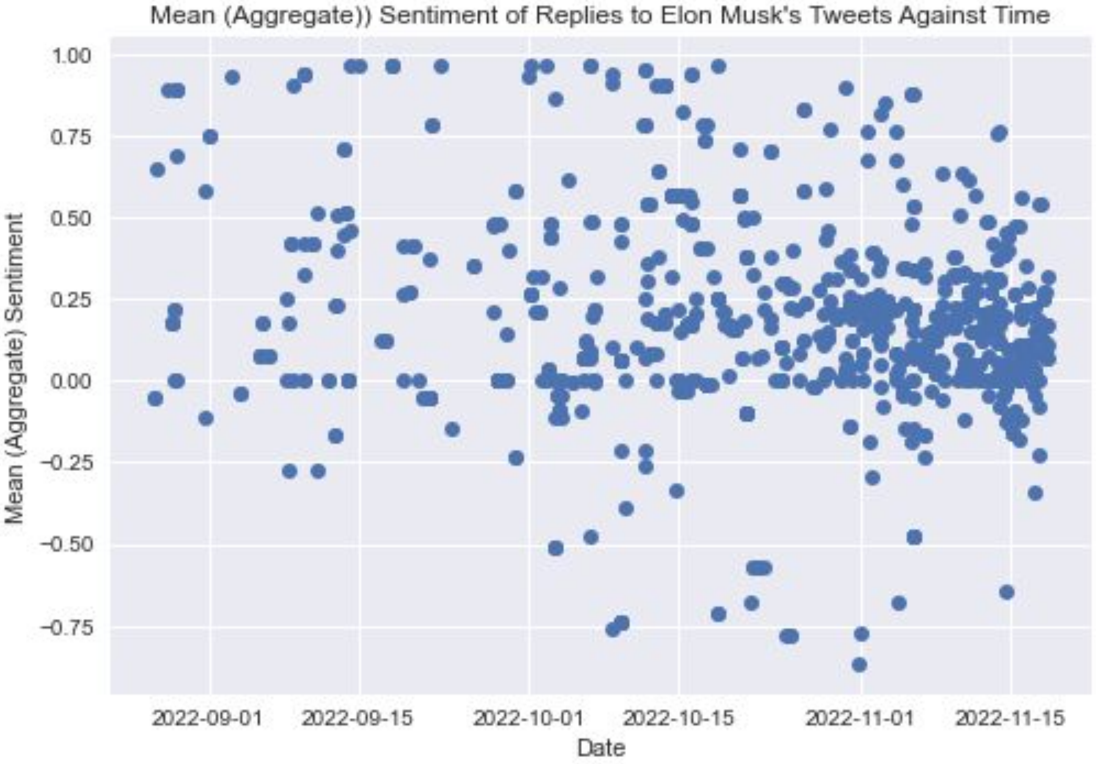
Argument 1: Following the takeover responses to his tweets have become more negative.

Evidence / Data: [VADER] Showcasing Mean (Compound) Sentiment Against Time

y_text	created_at	conversation_id_r	author_id	in_reply_to_user_id	id	edit_history_tweet_ids	mean_sentiment
musk ghOne urself!, ...	[2022-12-01T15:30:46.000Z, 2022-12-01T02:42:53...	[1590384919829962752, 1590384919829962752, 159...	[1126612002166587392, 1559857123504291840, 148...	[44196397, 44196397, 1481833905577598977, 1487...	[1598338825134252033, 1598145580043489280, 159...	[[1598338825134252033], [1598145580043489280],...	0.320283
@AOC nt. Are g du...	[2022-12-01T18:24:58.000Z, 2022-12-01T17:56:30...	[1593399168764190720, 1593399168764190720, 159...	[1554252246397120512, 1367206203223400452, 152...	[1586018719523737600, 765691822710542336, 3524...	[1598382663215108096, 1598375500602347538, 159...	[[1598382663215108096], [1598375500602347538],...	0.170420
esists musk sBlog o yo...	[2022-11-29T23:13:32.000Z, 2022-11-29T22:02:15...	[1593315850546618368, 1593315850546618368, 159...	[827536285359288324, 137390049, 15189969664448...	[739844197935644672, 44196397, 44196397, 44196...	[1597730509106204672, 1597712571410567168, 159...	[[1597730509106204672], [1597712571410567168],...	0.109579
organ hey're g to l...	[2022-12-01T14:05:15.000Z, 2022-12-01T14:04:10...	[1593521238915403776, 1593521238915403776, 159...	[1529757080986468352, 1529757080986468352, 829...	[216299334, 216299334, 216299334, 216299334, 2...	[1598317306119168003, 1598317033724301314, 159...	[[1598317306119168003], [1598317033724301314],...	0.069569
amino Looks u try...	[2022-12-01T14:02:47.000Z, 2022-12-01T02:45:26...	[1593494261038649344, 1593494261038649344, 159...	[1356751399409876992, 1359707307182022660, 158...	[1685873604, 44196397, 1594306080309387265, 44...	[1598316684573642754, 1598146224183742464, 159...	[[1598316684573642754], [1598146224183742464],...	0.274438

```
In [640]: def row_sentiment(row):
              analyzer = SentimentIntensityAnalyzer()
              count = row['replies_info'].get_count()
              if (count != 0):
                  compound_scores = np.zeros(count)
              else:
                  return np.nan
              for i in range(count):
                  text = row['replies_info'].get_replies()[i]['text']
                  #print(text)
                  vs = analyzer.polarity_scores(text)
                  compound_scores[i] = vs['compound']
                  #print(compound_scores[i])

              return np.mean(compound_scores)
```

Data and Approach

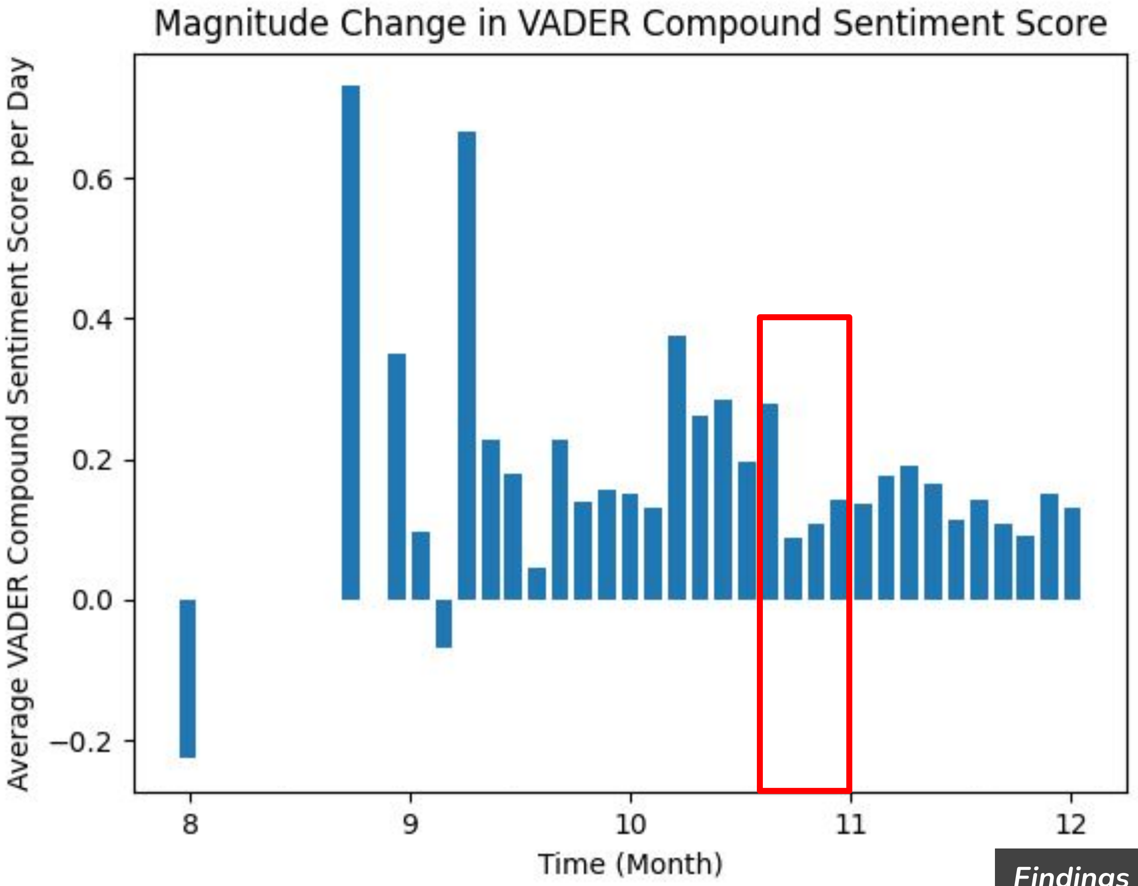


Key Takeaways

- Unequal distribution of data
- Tends downwards but cluttered result

Key Takeaways

- Over time, tweets have become more negative.
- Significant drop around the time of his acquisition.



Findings

Aggregate Sentiment Pre/Post-Takeover

[VADER]	**Pre-Takeover**	**Post-Takeover**
Mean (Aggregate) Sentiment	0.2133	0.1484
Standard Deviation	0.3610	0.2035

Key Takeaways

- The t-score (unequal variance [independent]) between the mean (aggregate) sentiments values is **3.3479**.
- A t-value > 3 indicates a large, significant difference exists between the two sample sets.

Argument 2: Feelings of *sadness*, *anger*, and *fear* intensify while feelings of *trust* dissipate.

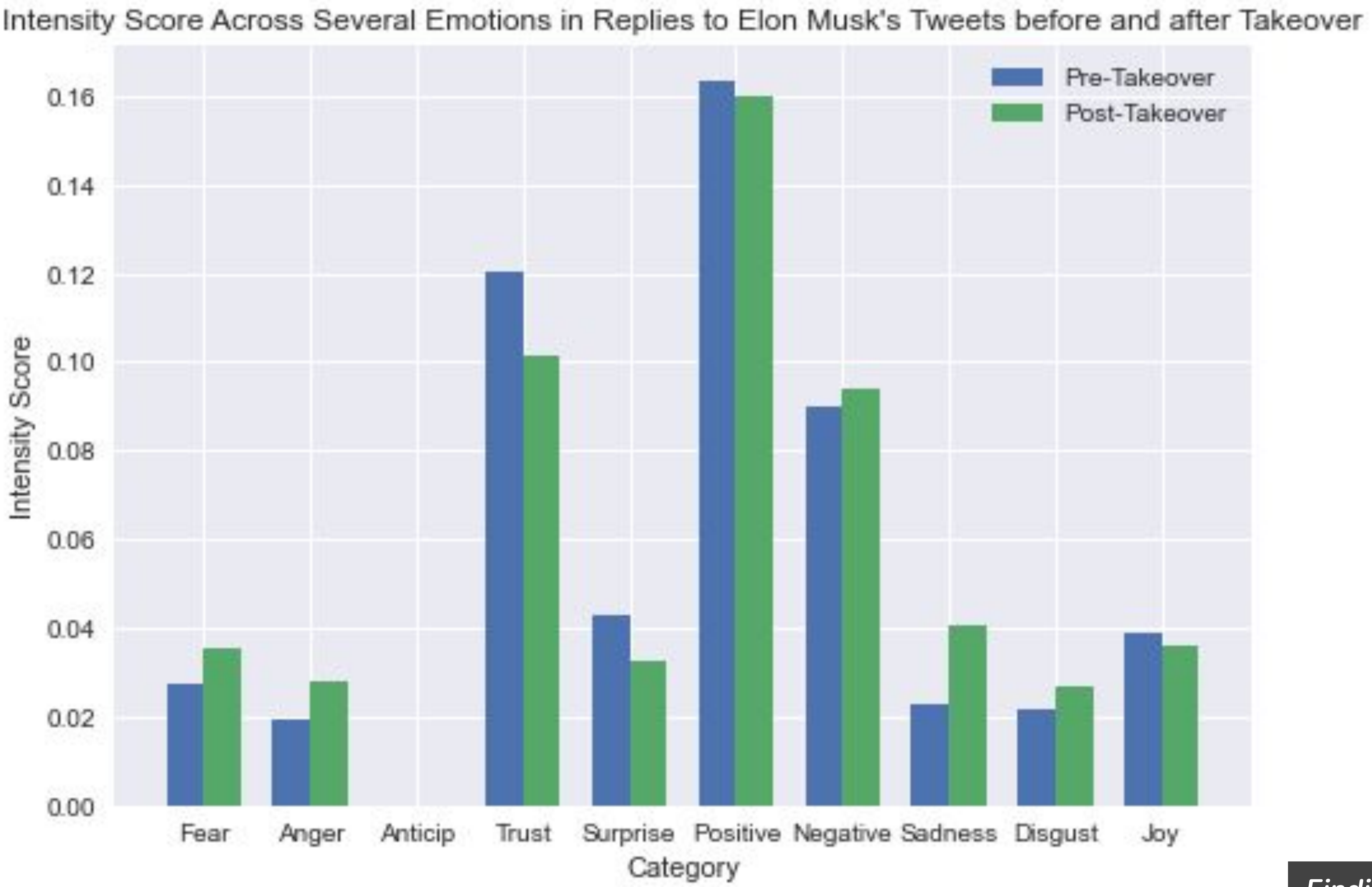
Evidence / Data: [NRCLex] Intensity Score Across Several Emotions Before and After the Takeover

```python
In [826]: from nrclex import NRCLex

          def emotion_sentiment(text):
              emotion = NRCLex(text)
              return emotion.affect_frequencies

          text = "I love this class!"
          emotion_sentiment(text)

Out[826]: {'fear': 0.0,
           'anger': 0.0,
           'anticip': 0.0,
           'trust': 0.0,
           'surprise': 0.0,
           'positive': 0.5,
           'negative': 0.0,
           'sadness': 0.0,
           'disgust': 0.0,
           'joy': 0.5}
```

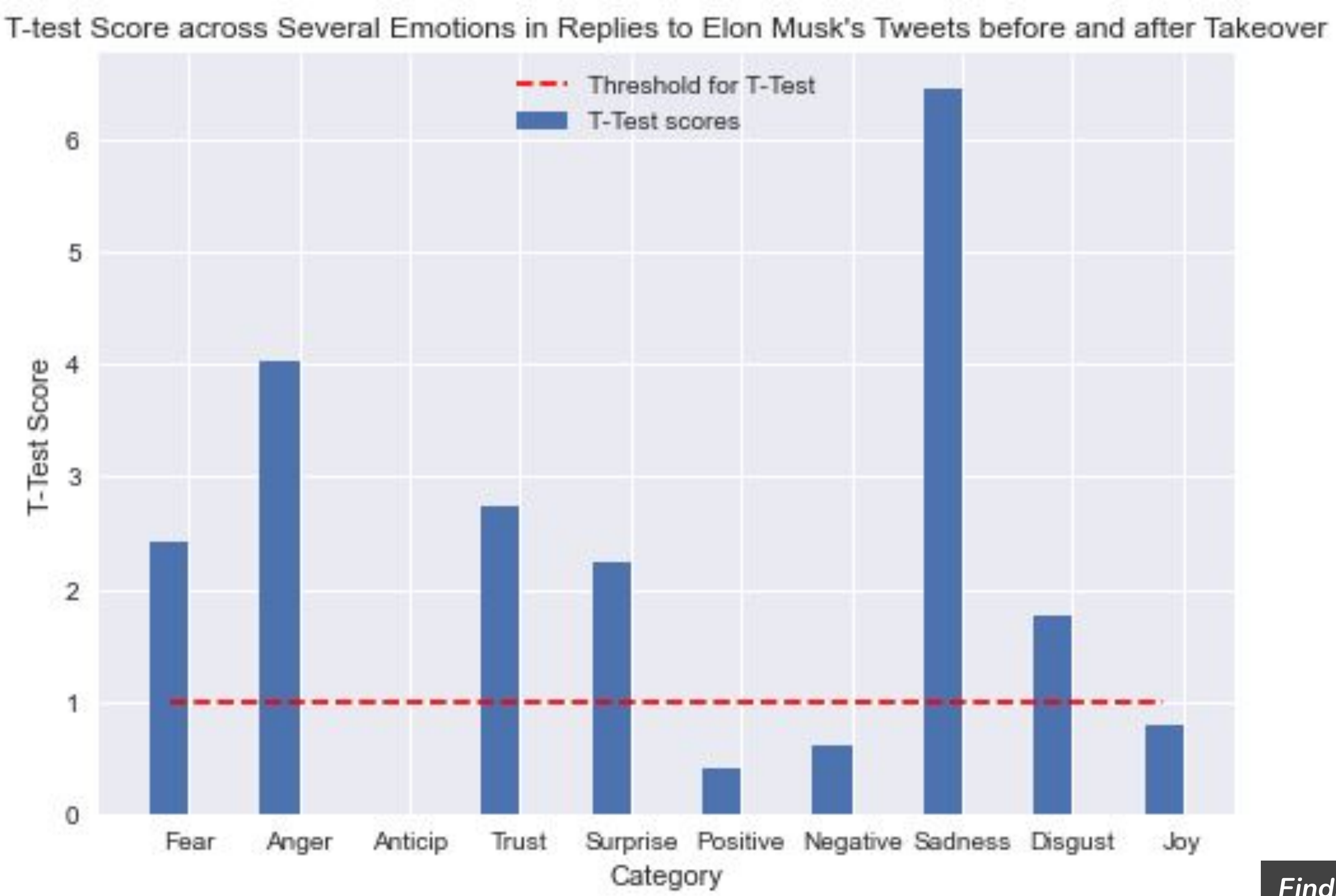
(on replies)

reply_text	created_at	conversation_id_r	...	fear	anger	anticip	trust	surprise	positive	negative	sadness	disgust	joy
[@elonmusk @Havi_HighOne Then fire yourself!, ...	[2022-12-01T15:30:46.000Z, 2022-12-01T02:42:53...	[1590384919829962752, 1590384919829962752, 159...	...	0.044603	0.030099	0.0	0.093202	0.066838	0.137655	0.090646	0.040785	0.026948	0.049008
[@Kroq44 @AOC You're right. Are you working du...	[2022-12-01T18:24:58.000Z, 2022-12-01T17:56:30...	[1593399168764190720, 1593399168764190720, 159...	...	0.036365	0.035335	0.0	0.069805	0.020330	0.183850	0.108621	0.037965	0.027566	0.038744
[@AmoneyResists @elonmusk @WholeMarsBlog Do yo...	[2022-11-29T23:13:32.000Z, 2022-11-29T22:02:15...	[1593315850546618368, 1593315850546618368, 159...	...	0.116071	0.008929	0.0	0.092262	0.008929	0.147817	0.077381	0.000000	0.023810	0.012401
[@piersmorgan @elonmusk They're not going to l...	[2022-12-01T14:05:15.000Z, 2022-12-01T14:04:10...	[1593521238915403776, 1593521238915403776, 159...	...	0.056410	0.056410	0.0	0.000000	0.026923	0.023077	0.129487	0.103846	0.030769	0.015385
@AngelaBelcamino @elonmusk Looks like you try...	[2022-12-01T14:02:47.000Z, 2022-12-01T02:45:26...	[1593494261038649344, 1593494261038649344, 159...	...	0.054446	0.043895	0.0	0.052532	0.040219	0.099773	0.1[illegible]	[illegible]	[illegible]	[illegible]

Data and Approach


Intensity Score Across Several Emotions in Replies to Elon Musk's Tweets before and after Takeover
Pre-Takeover
Post-Takeover
Intensity Score
0.16
0.14
0.12
0.10
0.08
0.06
0.04
0.02
0.00
Fear
Anger
Anticip
Trust
Surprise
Positive
Negative
Sadness
Disgust
Joy
Category

Findings


T-test Score across Several Emotions in Replies to Elon Musk's Tweets before and after Takeover
Threshold for T-Test
T-Test scores
T-Test Score
0
1
2
3
4
5
6
Fear
Anger
Anticip
Trust
Surprise
Positive
Negative
Sadness
Disgust
Joy
Category

Findings

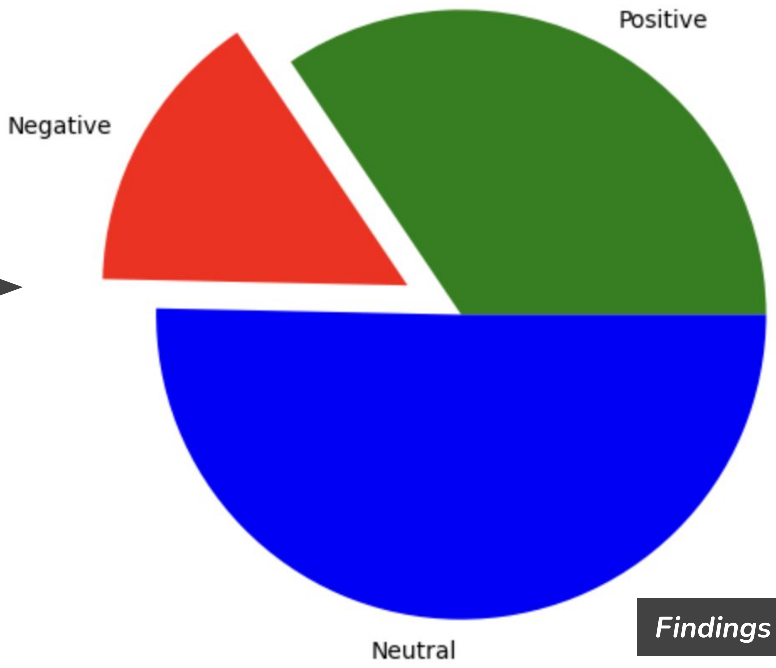
Argument 3: After the takeover users feel more *passionate* about Elon Musk's content, and interact with it more often.

Evidence / Data: [Statistical Analysis] Twitter Likes and Retweet Frequency.

STATISTICAL ANALYSIS

```
The tweet with more likes is: the bird is freed
Number of likes: 2479472
Time: 2022-10-28 03:49:11+00:00

The tweet with more retweets is: the bird is freed
Number of retweets: 352909
Time: 2022-10-28 03:49:11+00:00
```

```
Total Positive Replies % : 34.44
Total Negative Replies % : 15.23
Total Neutral Replies % : 50.33
```

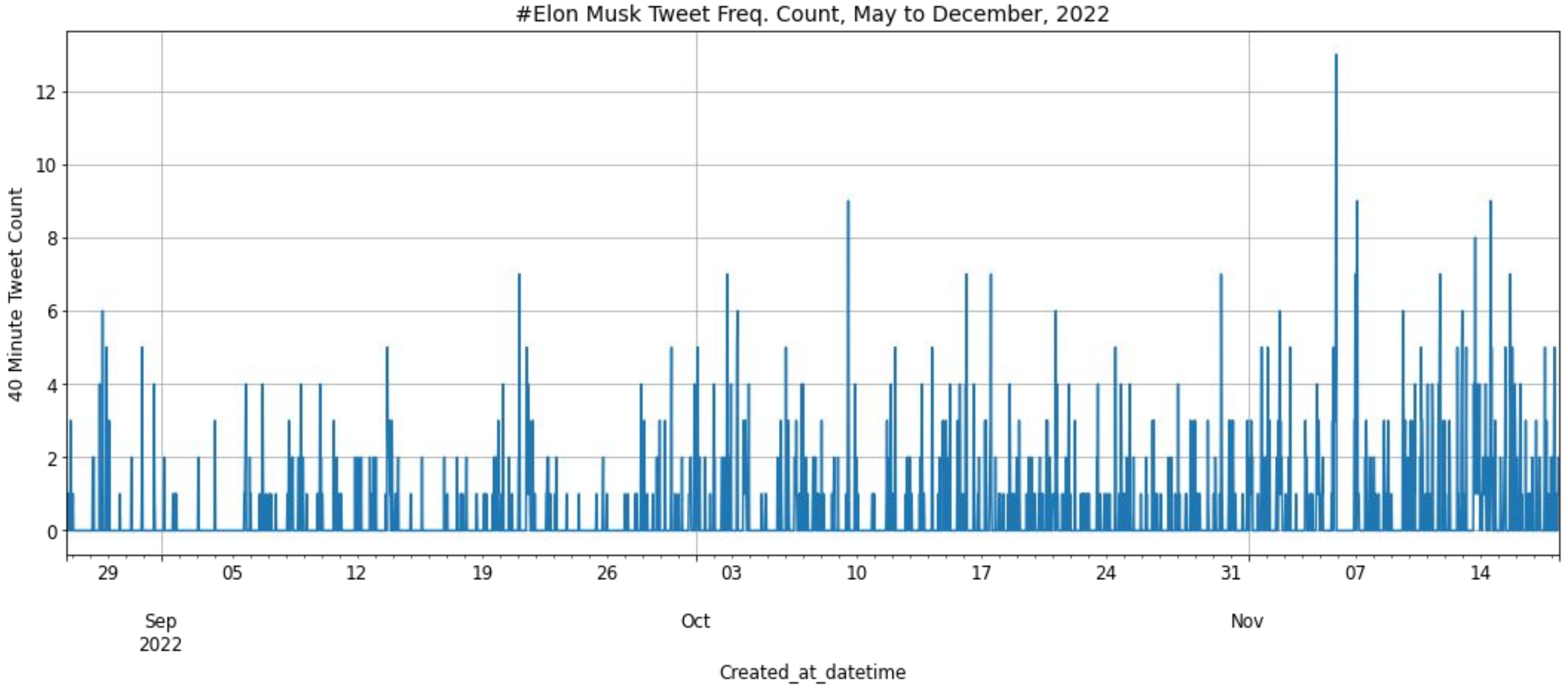


Sentimental Analysis of the replies to this specific tweet

Findings

ANALYZING MUSK'S ACTIVITY AND COMMUNITY INVOLVEMENT AFTER HIS TAKEOVER

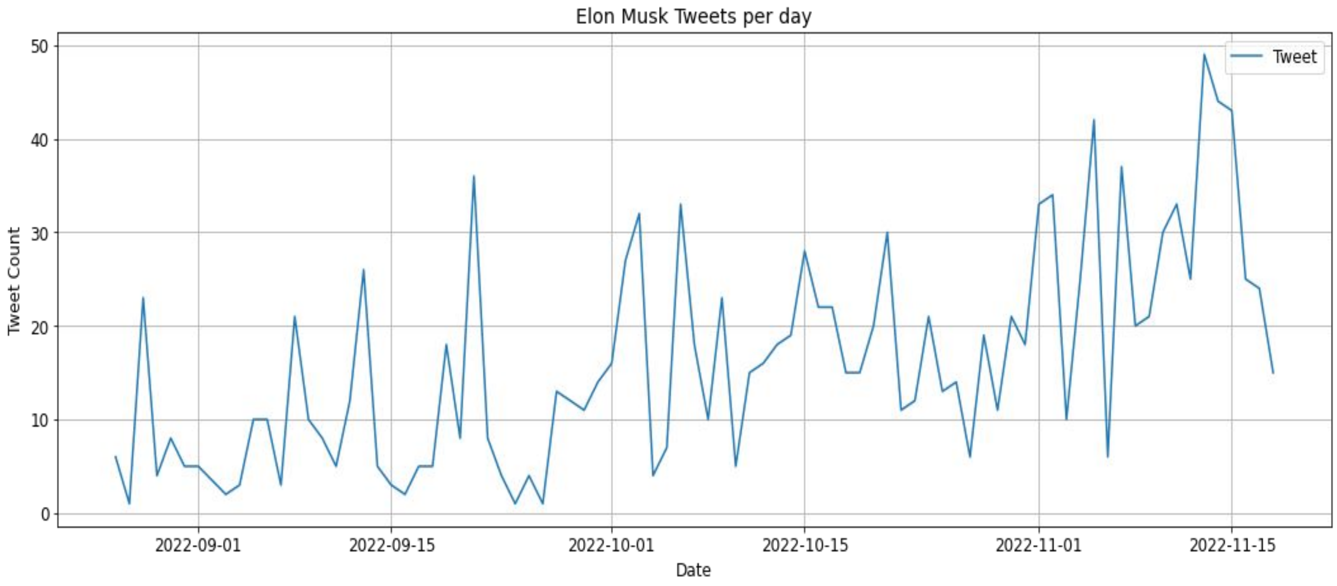
2.1. Musk's activity:



Findings

ANALYZING MUSK’S ACTIVITY AND COMMUNITY INVOLVEMENT AFTER HIS TAKEOVER

2.1. Musk’s activity:



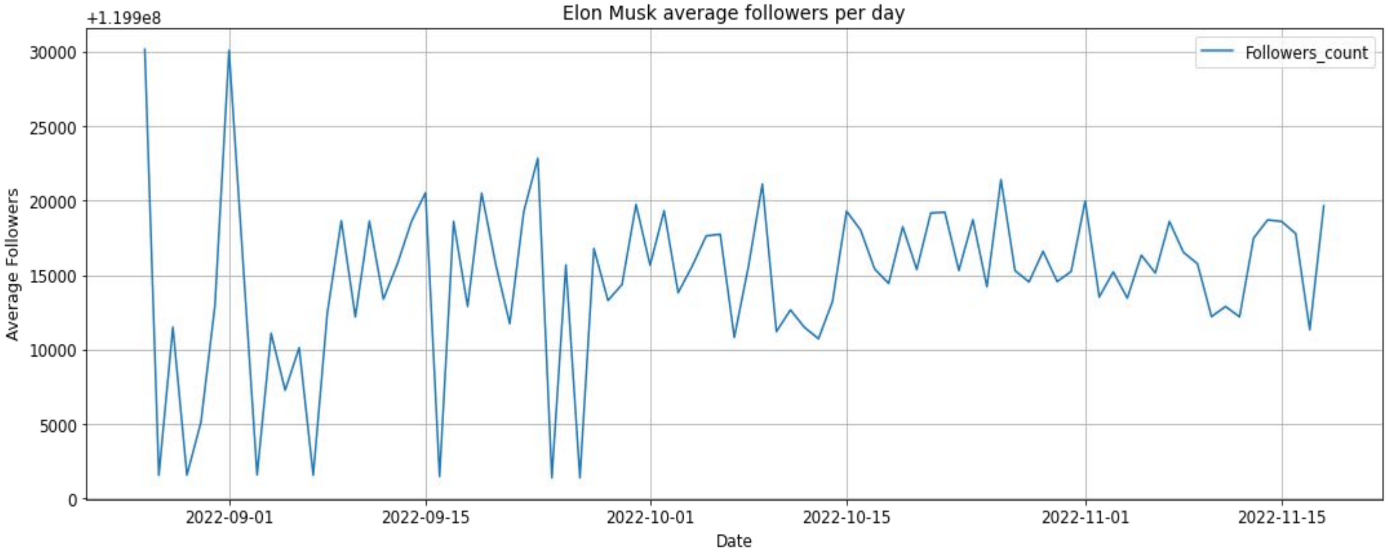
Key Takeaways

-> Elon Musk’s activity has significantly increased after the takeover

Findings

ANALYZING MUSK'S ACTIVITY AND COMMUNITY INVOLVEMENT AFTER HIS TAKEOVER

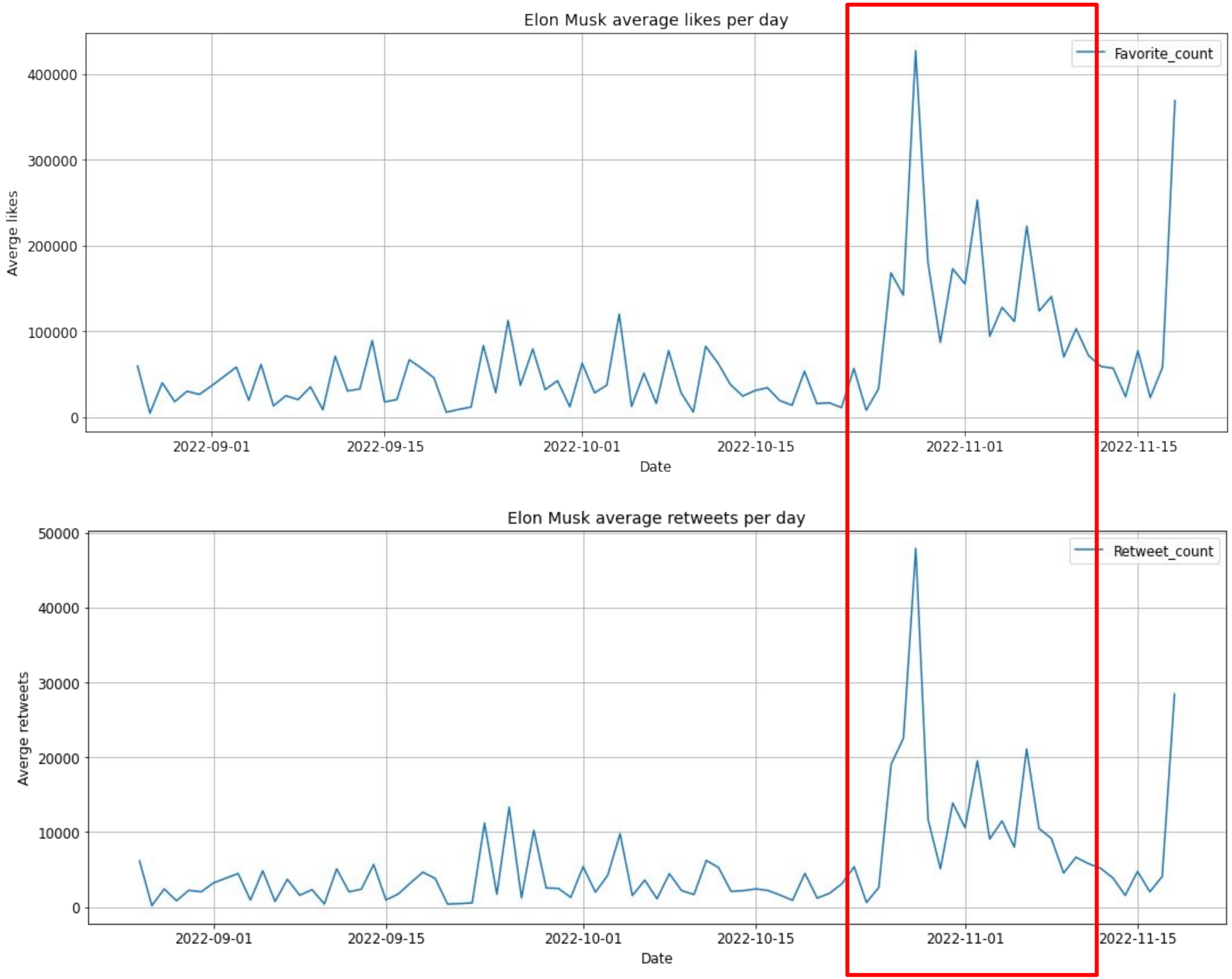
2. Community involvement:
    1. Average followers per day
    2. Average Likes per day
    3. Average Retweets per day



Key Takeaways

-> Consistency in the number of followers around the takeover date

Findings



Key Takeaways

-> After the takeover people are more involved in Elon Musk's contents

-> People realize the importance of Elon Musk as an influential person and interact more

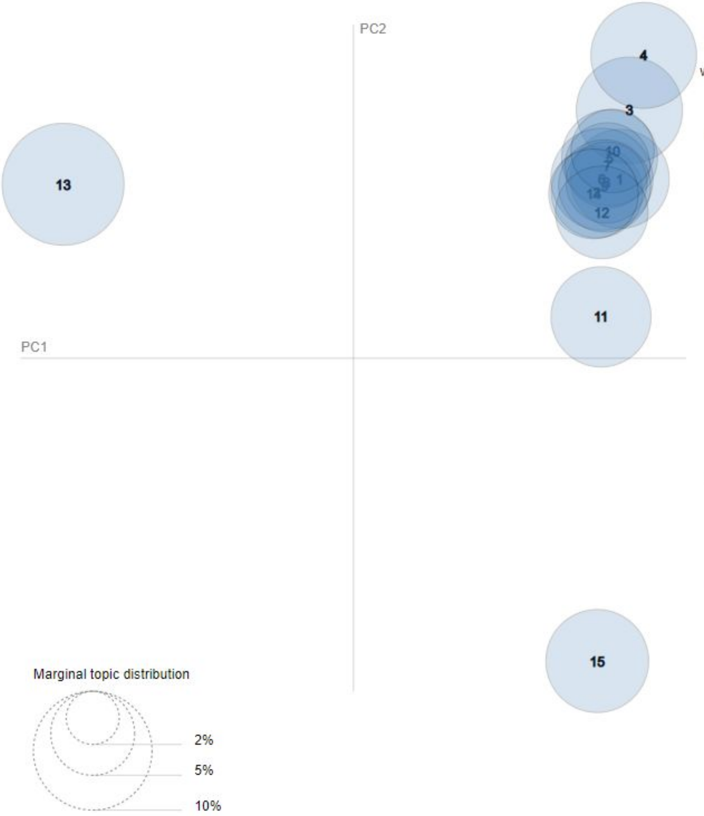
Findings

Limitations: We did not hold the topic/content of a tweet as a fixed variable.

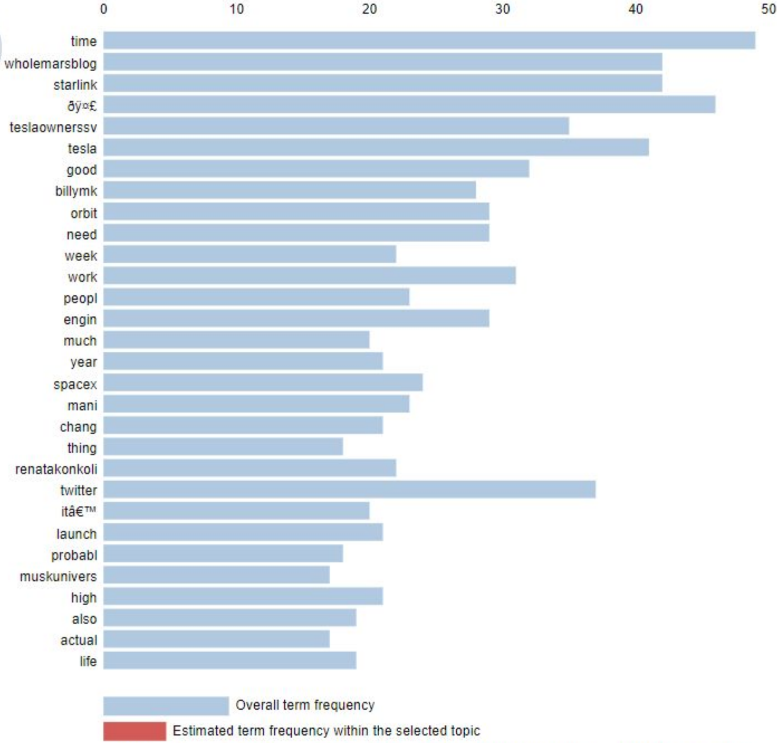
Evidence / Data: [Topical Analysis] Top 30 Most Relevant Terms in Tweets and Replies.

Possible Criticisms / Weaknesses

Intertopic Distance Map (via multidimensional scaling)



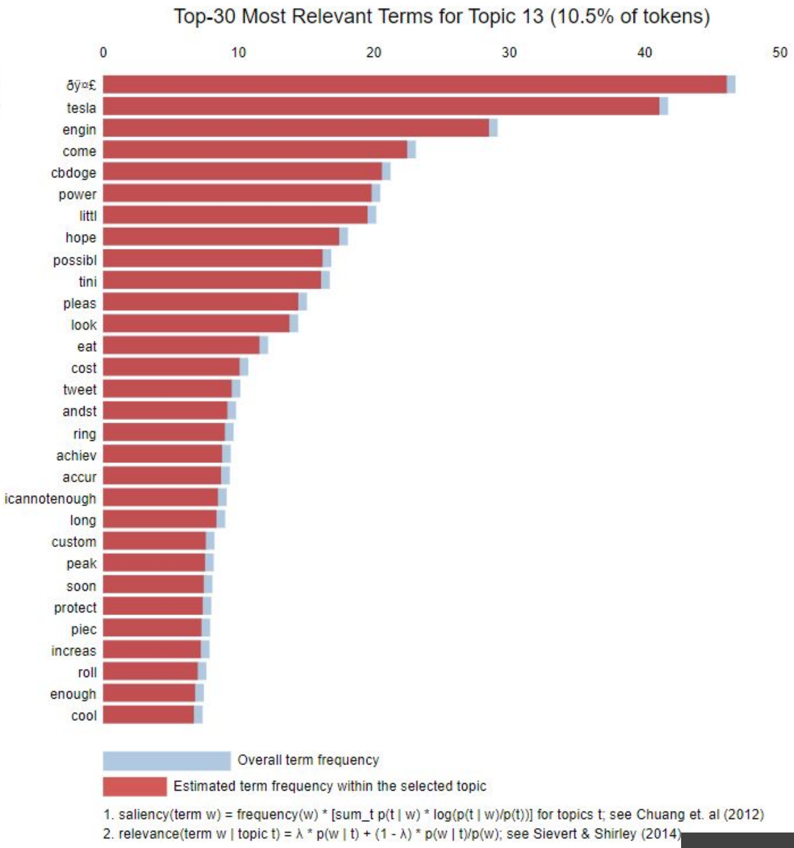
Top-30 Most Salient Terms[1]



1. saliency(term w) = frequency(w) * [sum_t p(t | w) * log(p(t | w)/p(t))] for topics t; see Chuang et. al (2012)
2. relevance(term w | topic t) = λ * p(w | t) + (1 - λ) * p(w | t)/p(w); see Sievert & Shirley (2014)

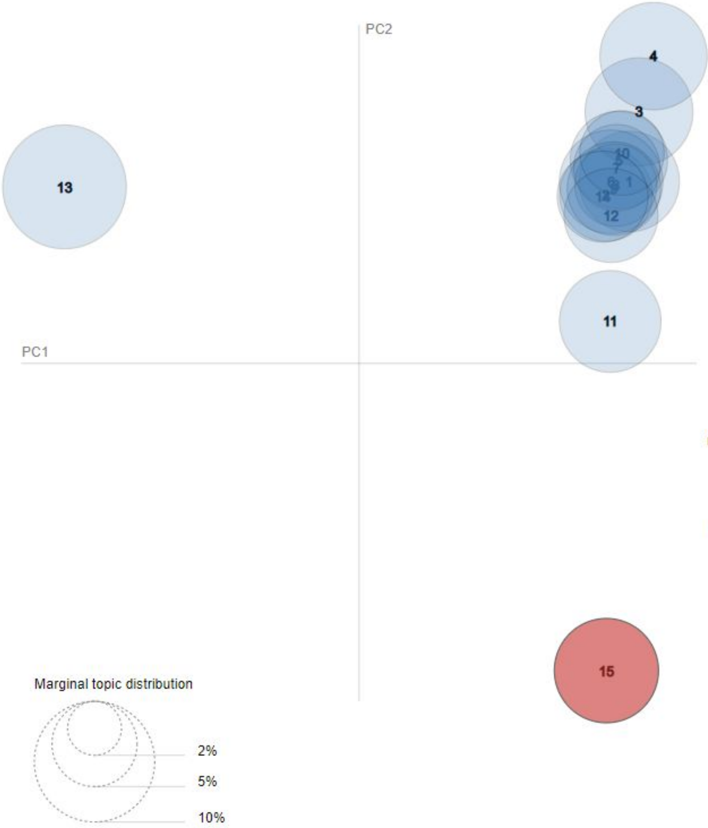
Findings


Intertopic Distance Map (via multidimensional scaling)
PC2
PC1
4
3
10
7
1
12
13
11
15
Marginal topic distribution
2%
5%
10%

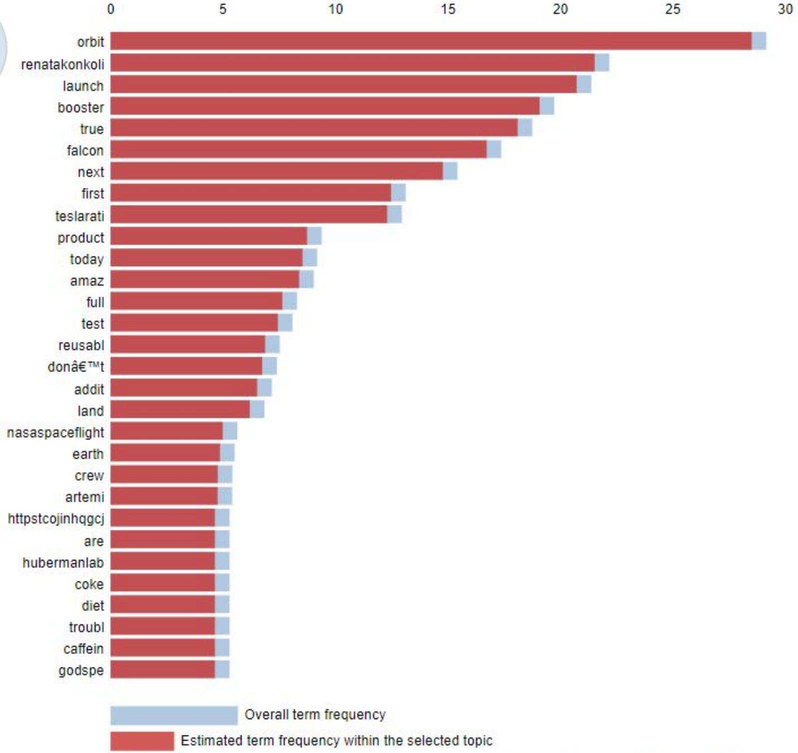

Top-30 Most Relevant Terms for Topic 13 (10.5% of tokens)
0
10
20
30
40
50
ðÿ¤£
tesla
engin
come
cbdoge
power
littl
hope
possibl
tini
pleas
look
eat
cost
tweet
andst
ring
achiev
accur
icannotenough
long
custom
peak
soon
protect
piec
increas
roll
enough
cool
Overall term frequency
Estimated term frequency within the selected topic
1. saliency(term w) = frequency(w) * [sum_t p(t | w) * log(p(t | w)/p(t))] for topics t; see Chuang et. al (2012)
2. relevance(term w | topic t) = λ * p(w | t) + (1 - λ) * p(w | t)/p(w); see Sievert & Shirley (2014)

Findings

Intertopic Distance Map (via multidimensional scaling)

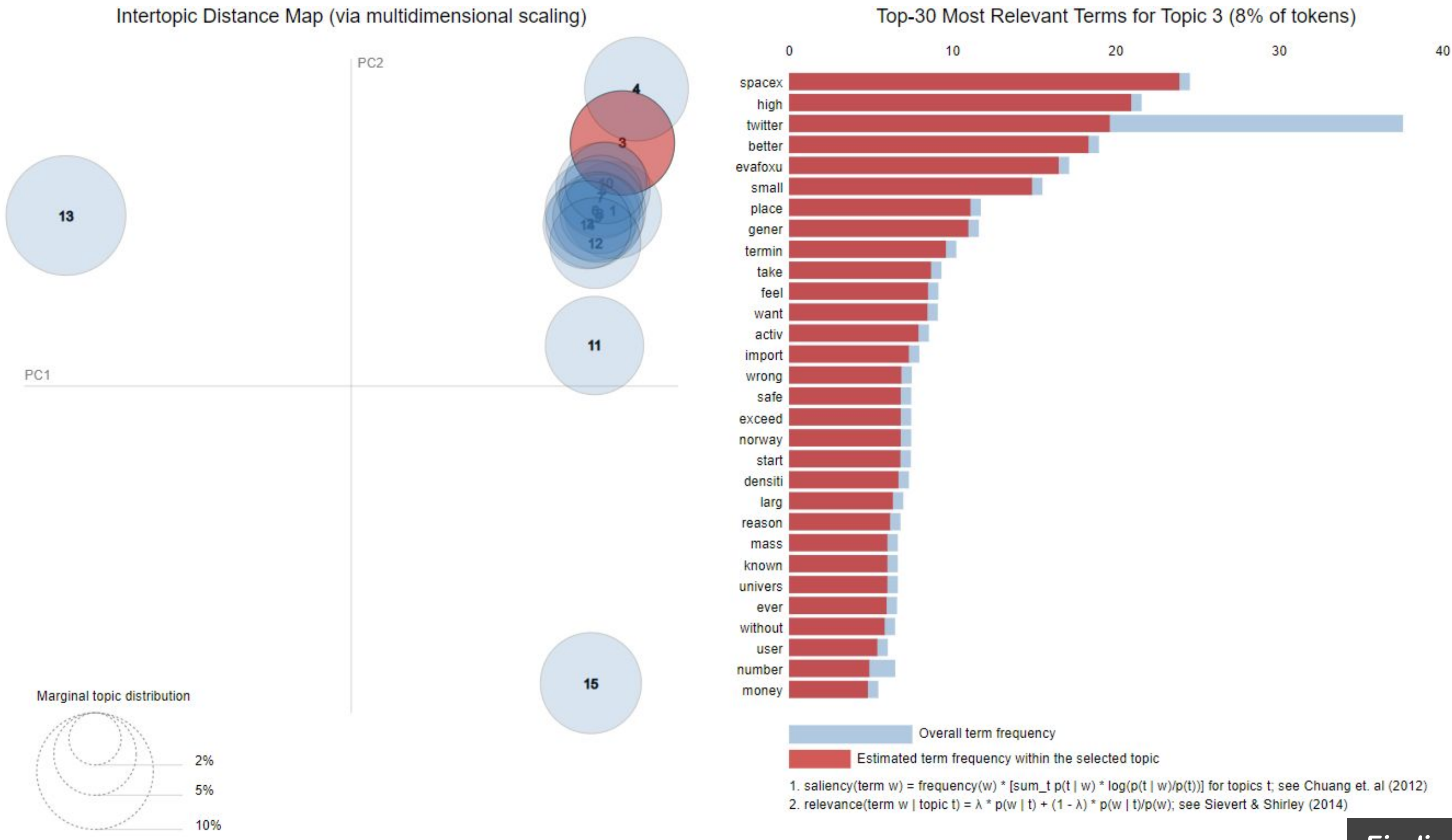


Top-30 Most Relevant Terms for Topic 15 (7.5% of tokens)



1. saliency(term w) = frequency(w) * [sum_t p(t | w) * log(p(t | w)/p(t))] for topics t; see Chuang et. al (2012)
2. relevance(term w | topic t) = λ * p(w | t) + (1 - λ) * p(w | t)/p(w); see Sievert & Shirley (2014)

Findings


Intertopic Distance Map (via multidimensional scaling)
PC2
PC1
4
3
13
10
7
6
1
14
12
11
15
Marginal topic distribution
2%
5%
10%
Top-30 Most Relevant Terms for Topic 3 (8% of tokens)
0
10
20
30
40
spacex
high
twitter
better
evafoxu
small
place
gener
termin
take
feel
want
activ
import
wrong
safe
exceed
norway
start
densiti
larg
reason
mass
known
univers
ever
without
user
number
money
Overall term frequency
Estimated term frequency within the selected topic
1. saliency(term w) = frequency(w) * [sum_t p(t | w) * log(p(t | w)/p(t))] for topics t; see Chuang et. al (2012)
2. relevance(term w | topic t) = λ * p(w | t) + (1 - λ) * p(w | t)/p(w); see Sievert & Shirley (2014)

Findings

Limitations: There are certain limitations related to the Twitter API, for instance:

- Time Limitations
- Elevated Access vs Research / Full Archival Search Access

Possible Criticisms / Weaknesses

Conclusion/Implications: These are the implications to our main arguments:

Argument 1: [VADER] Shifting the sentiment of responses to his tweets towards being more negative.

Argument 2: [NRCLex] Intensifying feelings of "sadness", "anger", and "fear" while dissipating feelings of "trust".

Argument 3: [Statistics] After the takeover users feel more passionate about Elon Musk's content, and interact with it more often.

Argument 1 & **Argument 2** Openness —

The climate has changed on Twitter, and this can potentially impact the **perception** of "openness" on Twitter.

Argument 3: Participation —

The importance of this event, and how much of it was influenced by Twitter, has demonstrated the amount of **leverage** someone can have by participating on Twitter.