Parallel Worlds

Francesco Prem Solidoro, Michele Salvi

Table of contents

1 Parallel Worlds - a View of Social Media Manipulation and Polarization

- Michele Salvi / michele.salvi4@studio.unibo.it / 0001082457
- Francesco Prem Solidoro / francesco.solidoro@studio.unibo.it / 0001071898

1.1 Abstract

What is truth? It can be argued that truth is but the set of facts we intersubjectively agree to be correct as a society. In this view, while voices of specialists hold power sway, it's ultimately public opinion that shapes the shared ground over which political discourse and policy are built. It immediately becomes apparent that choosing one's terrain is a powerful tool in achieving one's objectives. To that end, it becomes essential to:

- win over people to believe in your cause
- make sure people you won over don't leave for other causes.

In comes "Parallel Worlds".

There's no stronger attack against opposing ideas than die-hard fans, and no defense more solid than said die-hard fans *never being exposed to competing ideas.* The pursuit for achieving a parallel

world with a Truth that's centralised is an old one: think of Mussolini and Hitler's use of radio. The renewed threat coming from it is that we're coming off of a new media revolution: just like the printing press, the radio and the television before it, the internet has radically changed the way information flows through society. Analogously, with this revolution, new paradigms of communication have burst into the scene, alongside methods for manipulation of information. The Internet has the unique property of allowing anyone to have a voice, and therefore to represent in an uncanny way the dynamics of social conversation, where not only the loudest, but also the most numerous voices dominate. In this there's an inherit democratic principle of attention being divided equally through society. In this there's also an inherent danger: with bots and technological advancement, it's become easy to artificially boost ideas to favour an agenda through a faux legitimisation from a virtual majority. With the objective of enclosing people who believe they're engaged in an open network into a closed down bubble of ideas, thus spawns the Astroturf. A successful astroturf will appear to be grassroots support for an idea, while driving polarisation to a point where those in support and those in opposition to the target idea will effectively live in different, parallel worlds. With all contact being auspicably hostile: demonisation of the other side, deification of one's one, discreditation of third party "experts". These are all hallmarks of astroturf campaigns, and they're more and more visible within modern society, as this camoflauged threat rips the promise of the open internet into bubbles floating in the sea of its former potential.

1.2 Introduction

The topic of manipulation has long been studied by scholars in its different facets, and in this paper we'll explore the connection between the political sphere and manipulation when used as an instrument to achieve control.

In the last years social media usage has skyrocketed (Esteban Ortiz-Ospina, n.d.), thus more advanced methods of manipulating public opinion, both in and outside the political sphere, have arisen due to the innovations and reach that social media platforms boast. Historically, the preferred outcome of manipulation has always been polarization, giving rise to strong leaders and divides (Jacob et al., n.d.).

The Merriam-Webster dictionary defines polarization (*Merriam-Webster*, n.d.) as "a state in which the opinions, beliefs, or interests of a group or society no longer range along a continuum but become concentrated at opposing extremes", it's a key factor to view polarization as an outcome rather than a means, since it's always been the objective of different political parties to achieve their goals. Now, in this era of limitless communication, one would see complete polarization as harder to achieve, due to the sheer amount of different opinions available on social media, but there's a new, and arguably the worst ever, means of achieving a polarized society: astroturfing.

Astroturfing is defined by the Merriam-Webster dictionary (*Merriam-Webster*, n.d.) as "organized activity that is intended to create a false impression of a widespread, spontaneously arising, grassroots movement in support of or in opposition to something but that is in reality initiated and controlled by a concealed group or organization". Such a practice is deeply deceptive and thrives on platforms like social media, where identity can be disguised and allegiance faked, to distort and manipulate public opinion.

Astroturfing can be declined into two further classifications, *commercial astroturfing*, centered around the accumulation of profit, and *political astroturfing*, concerned with the attainment of political objectives. Research on political astroturfing has become increasingly present in the last years, and it mainly focuses on analyzing its effects on politics, highlighting the power that this practice represents by exposing its presence in (but not limited to) South Korea's 2012 Presidential Elections (Franziska B. Keller et al., n.d.), the USA's 2016 elections (Ahmed & Anis Rahman, n.d.) and faking Chinese Social media posts (Gary et al., n.d.). These papers highlight the real-world effects and the seriousness of groups and/or individuals rich in economic and social capital, who seek to manipulate public opinion to achieve private objectives, especially in politics, putting them in commanding positions.

The idea behind the "parallel worlds" is that polarization through astroturfing acts silently and unbeknownst to the population, creating fissures and fragmentation in public opinion that effectively alienate and polarize society. The preferred medium for this practice is, as previously stated, through social media, so we focused on the biggest and most documented instance of astroturfing, the 2016 USA elections.

1.3 Research Question

In our pursuit of understanding how parallel worlds are built, we have to understand two things:

- what makes an astroturf?
- what effect does it actually have?
- is it possible to generalize and model an astroturfing from the words used?

  To understand this, we will be conducting a sentiment analysis over the datasets of IRA-affiliated tweets utilizing text mining practices such as word frequencies, tf-idf, sentiment analysis through the NRC (*NRC Lexicon*, n.d.), Bing (*Mining and Summarizing Customer Reviews*, n.d.) and AFINN (*AFINN Lexicon*, n.d.) lexicons, and the aid of LDA, latent dirichlet allocation, to model the topics discussed in the tweets.

1.3.a Downloading, Importing, merging and cleaning the dataset

We got the following datasets from 538's github, which were merged into a single dataset.

Since the analysis is quite taxing, we're going to sample 100.000 tweets to perform a preliminary analysis on. In order to conduct the analysis on the full dataset, remove the following block.

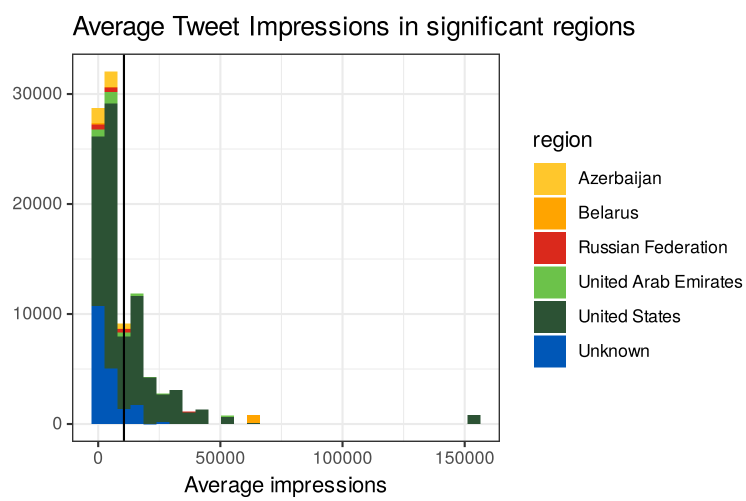
The cleaned and merged dataset contains the following variables:

- **author**: the author of the tweet, categorical
- **content**: the content (text) of the tweet, string
- **region**: the region in which the tweet "originated", if not specified it's marked as "Unknown", categorical
- **language**: the language in which the tweet was written , categorical
- **publish_date**: the date in which the tweet was published, date
- **following**: the number of accounts followed by the tweet author, numerical
- **followers**: the number of accounts that follow the tweet author, numerical

- **updates**: the number of impressions (likes, comments and retweets) summed, numerical
- **post_type**: the type of post (retweet / quote retweet / NA for normal tweets), categorical
- **account_type**: the type of account, previously set, by tweet content, categorical
- **retweet:** weather the tweet was a retweet or not, binary
- **account_category:** the accounts grouped by categories based on tweet content, categorical

To describe the dataset, we plotted a few graphs (some of which are attached, but not essential), showing the proportions of tweet by languages, by account types and by regions (not included in the pdf, code block above)

To represent tweets in proportion to their engagement, so effect on the population, we then plotted tweets by average impressions, according to the regions, highlighting the discrepancies, and different reception of the astroturfing in different regions.



As it can be observed in the graph, despite there being IRA-connected accounts in multiple regions, most of the interactions and impressions come from tweets from the united states.

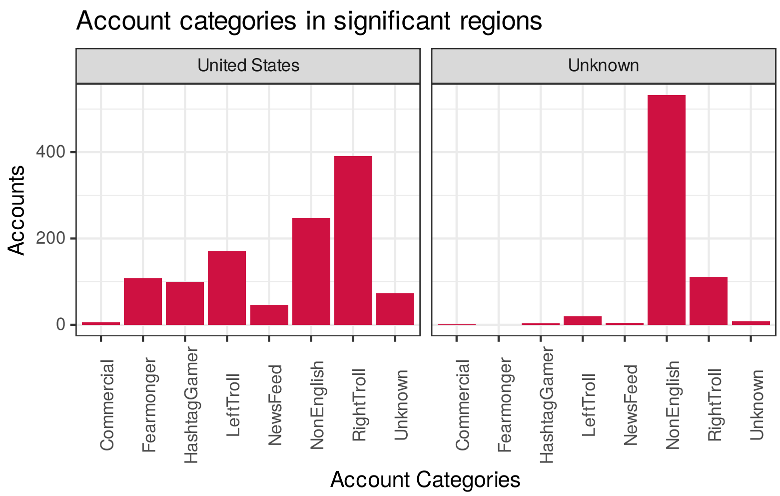
To represent well the most significant regions (United states, Unknown) we categorized the IRA-connected accounts by their type, so the macro-topic they covered in their tweets, along with the retweet rate and descriptive statistics on the follows and followers.

```
   vars     n    mean       sd median trimmed     mad min    max  range skew
X1    1 1e+05 7136.01 14879.11   1313 4089.26 1761.33   0 251245 251245 6.01
   kurtosis    se
X1    59.23 47.05
```

```
   vars     n    mean      sd median trimmed     mad min   max range skew
X1    1 1e+05 3456.67 5564.75   1528 2365.65 2043.02   0 76206 76206 5.12
   kurtosis   se
X1    46.52 17.6
```

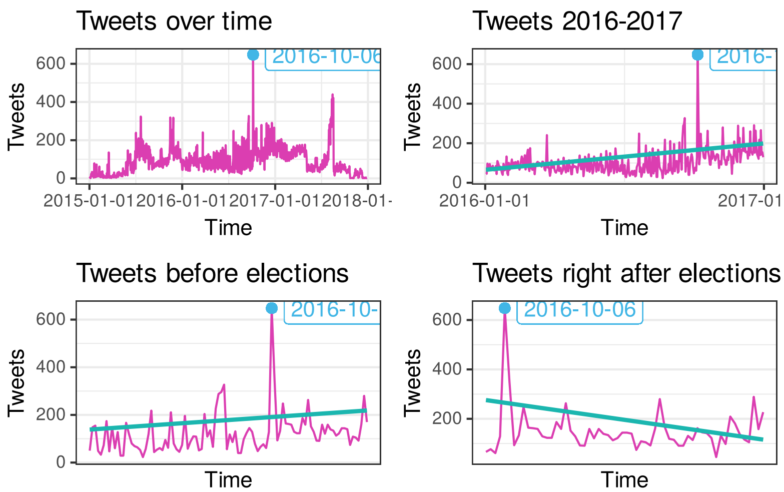
```
[1] 0.44007
```

```
# A tibble: 8 × 2
  account_category retweet_rate
  <chr>                   <dbl>
1 LeftTroll             0.820
2 HashtagGamer          0.715
3 NonEnglish            0.548
4 RightTroll            0.437
5 Unknown               0.191
6 Fearmonger            0.148
7 Commercial            0.0638
8 NewsFeed              0.00188
```



Most of the accounts in the tweets can be traced back to either the US or the "Unknown" region, but since most accounts in this last region are "NonEnglish", we'll discard those and focus on those composed in English for most of our analysis.

Additionally, since the times at which the tweets were posted are included in the dataset, we plot them, progressively restricting them on the date of the presidential election, to have a look at the patterns.



As it can be observed, tweets steadily increased until a few days after the election, when they started dropping.

1.4 Analysis

1.4.a Text analysis

We began our analysis by focusing on the tweet's text. In this type of "word" centered approach we filtered the tweets to contain only English tweets, removing links and "stop words" (words such as the,a , by...) that would just hinder the process.

We then tokenized the tweets by words, by splitting each word in the content while homogenizing the text.

```
# A tibble: 75,862 × 2
   word         n
   <chr>    <int>
 1 news      5176
 2 trump     4840
 3 police    1875
 4 sports    1771
 5 people    1746
 6 world     1504
 7 politics  1500
 8 obama     1477
 9 workout   1473
10 amp       1366
# ℹ 75,852 more rows
```

```
# A tibble: 75,862 × 7
   word     NewsFeed RightTroll Commercial LeftTroll HashtagGamer Fearmonger
   <chr>       <int>      <int>      <int>     <int>        <int>      <int>
```

```
 1 news          4276        712          2        147            35           4
 2 trump          645       3317          1        705           166           6
 3 sports        1642         87          3         31             7           1
 4 workout         NA          1       1465          4             3          NA
 5 politics      1293        146          1         41            19          NA
 6 police        1173        310         NA        370            15           7
 7 obama          231       1075         NA        141            29           1
 8 world         1017        275          7        147            55           3
 9 breaking       224       1001          1         65            10          NA
10 hillary         64        931          1         72            52           3
# ℹ 75,852 more rows
```

```
# A tibble: 6 × 5
  account_category word          n    tot percent_freq
  <chr>            <chr>    <int>  <int>        <dbl>
1 NewsFeed         news      4276 145246        2.94
2 RightTroll       trump     3317 180769        1.83
3 NewsFeed         sports    1642 145246        1.13
4 Commercial       workout   1465  35869        4.08
5 NewsFeed         politics  1293 145246        0.890
6 NewsFeed         police    1173 145246        0.808
```

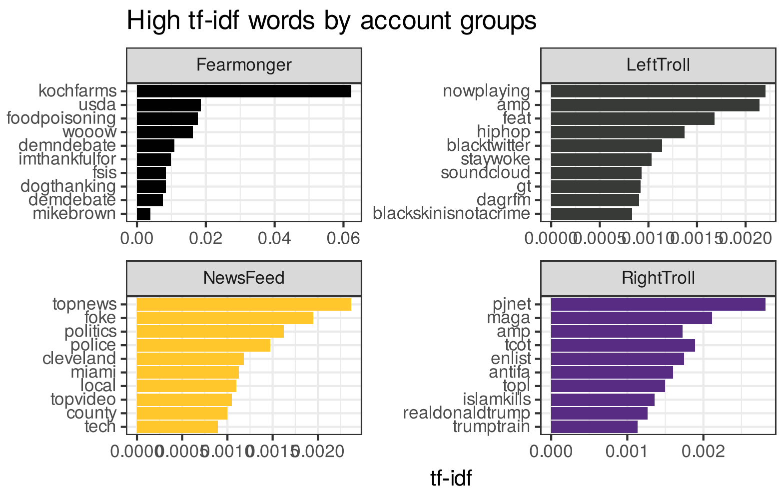
The most common words in the tweets are "news", "trump" and "police", by grouping the words by account we can see that those words are fairly common also by controlling for the different account types, further confirmed by the percentage frequencies of the same words.

Then we analyzed the word's tf-idf, the term frequency-inverse document frequency, which is a measure that assigns lower weight to words that are frequently used and a higher one to the uncommon ones.

The idea is to find a middle point between the two, as some words may be important to describe a text, while not being the most commonly used.

```
# A tibble: 74,759 × 7
   account_category word              n percent_freq      tf   idf  tf_idf
   <chr>            <chr>         <int>        <dbl>   <dbl> <dbl>   <dbl>
 1 Fearmonger       kochfarms       127        5.66  0.0566  1.10  0.0622
 2 Fearmonger       usda             60        2.67  0.0267  0.693 0.0185
 3 Fearmonger       foodpoisoning    36        1.60  0.0160  1.10  0.0176
 4 Fearmonger       wooow            33        1.47  0.0147  1.10  0.0162
 5 Fearmonger       demndebate       35        1.56  0.0156  0.693 0.0108
 6 Fearmonger       imthankfulfor    20        0.892 0.00892 1.10  0.00980
 7 Fearmonger       dogthanking      17        0.758 0.00758 1.10  0.00833
 8 Fearmonger       fsis             17        0.758 0.00758 1.10  0.00833
 9 Fearmonger       demdebate        24        1.07  0.0107  0.693 0.00742
```

```
10 Fearmonger       mikebrown         8        0.357 0.00357 1.10  0.00392
# ℹ 74,749 more rows
```



The high tf-idf words, plot by account category, highlight common topics to the 2016 elections and other high impact words (some of which were previously hashtags, but were included to not forego any information) like "islam kills", "black skin is not a crime", "food poisoning", and "stay woke".

1.4.b Bi-gram Analysis

Tokenization isn't only possible at the singular worlds level, we can tokenize according to "n-grams", which are series of n words.

We decided to focus on Bigrams, series of 2 words, and repeat some of the previous text analysis.

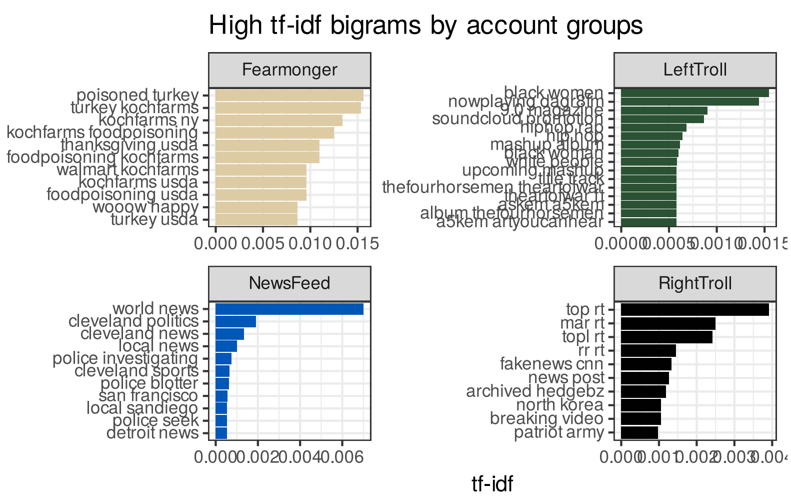
```
# A tibble: 215,978 × 3
   word1     word2       n
   <chr>     <chr>   <int>
 1 world     news      928
 2 donald    trump     462
 3 white     house     321
 4 hillary   clinton   270
 5 lose      weight    235
 6 president trump     218
 7 top       rt        217
 8 north     korea     197
 9 fake      news      147
10 local     news      143
# ℹ 215,968 more rows
```

This gives us additional context on the most common words, like "world news" and "donald trump"

We can also repeat the tf_idf analysis with bigrams to capture additional context that might have been discarded by single-word analysis.

```
# A tibble: 226,201 × 6
   account_category bigram                          n      tf   idf  tf_idf
   <chr>            <chr>                       <int>   <dbl> <dbl>   <dbl>
 1 Fearmonger       poisoned turkey                10 0.00873  1.79 0.0156
 2 Fearmonger       turkey kochfarms               16 0.0140   1.10 0.0153
 3 Fearmonger       kochfarms ny                   14 0.0122   1.10 0.0134
 4 Fearmonger       kochfarms foodpoisoning         8 0.00698  1.79 0.0125
 5 Fearmonger       foodpoisoning kochfarms         7 0.00611  1.79 0.0109
 6 Fearmonger       thanksgiving usda               7 0.00611  1.79 0.0109
 7 Fearmonger       foodpoisoning usda             10 0.00873  1.10 0.00959
 8 Fearmonger       kochfarms usda                 10 0.00873  1.10 0.00959
 9 Fearmonger       walmart kochfarms              10 0.00873  1.10 0.00959
10 Fearmonger       turkey usda                     9 0.00785  1.10 0.00863
# ℹ 226,191 more rows
```

Again, bigrams like "poisoned turkey", "isis accounts", reveal patterns that weren't captured by the previous tf-idf plot



Additionally, the bigram combinations can be plot in a network graph:

Combinations of words in bigrams

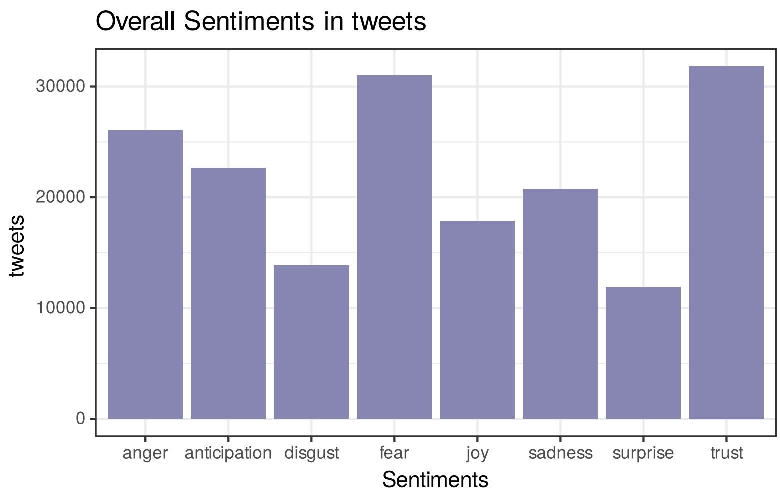
Arrows represent directional relationships between pairs of words, and distance is irrelevant.

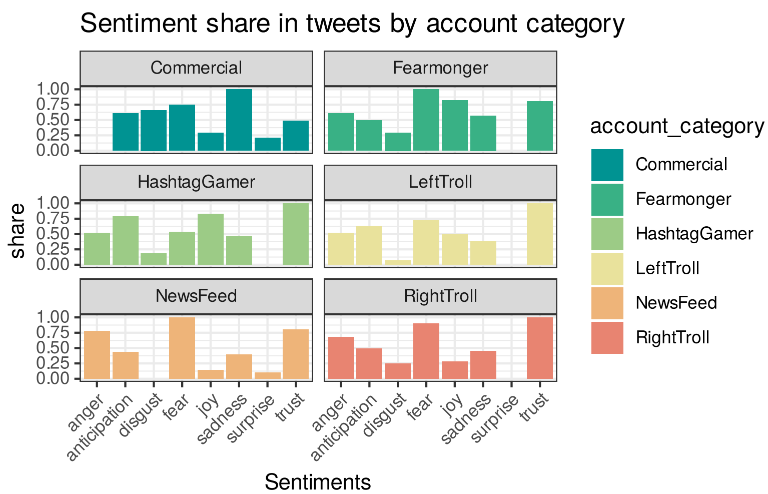
1.4.c Sentiment Analysis

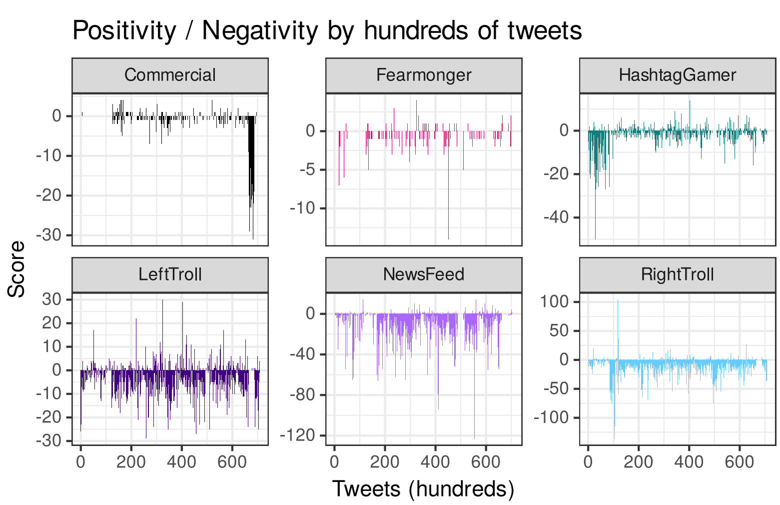
Sentiment analysis is a text analysis practice that assigns single words to sentiments as a method to interpret the emotion and feeling that a word is trying to convey.

This block filters out the word “trump” (to avoid misinterpretation in sentiment analysis) and joins the dataset with the NRC sentiment lexicon to classify words into sentiment categories. The result is a dataset of words with assigned sentiments.

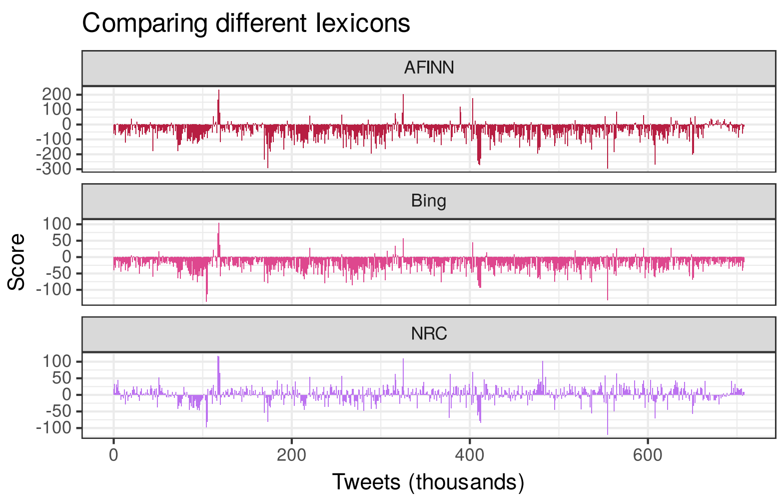
```
# A tibble: 26,765 × 6
   account_category word          n    tot percent_freq sentiment
   <chr>            <chr>     <int>  <int>        <dbl> <chr>
 1 NewsFeed         politics   1293 145246        0.890 anger
 2 NewsFeed         police     1173 145246        0.808 fear
 3 NewsFeed         police     1173 145246        0.808 positive
 4 NewsFeed         police     1173 145246        0.808 trust
 5 RightTroll       president   632 180769        0.350 positive
 6 RightTroll       president   632 180769        0.350 trust
 7 NewsFeed         shooting    471 145246        0.324 anger
 8 NewsFeed         shooting    471 145246        0.324 fear
 9 NewsFeed         shooting    471 145246        0.324 negative
10 RightTroll       time        454 180769        0.251 anticipation
# ℹ 26,755 more rows
```


Overall Sentiments in tweets
tweets
30000
20000
10000
0
anger
anticipation
disgust
fear
joy
sadness
surprise
trust
Sentiments


Sentiment share in tweets by account category
share
Commercial
Fearmonger
HashtagGamer
LeftTroll
NewsFeed
RightTroll
1.00
0.75
0.50
0.25
0.00
anger
anticipation
disgust
fear
joy
sadness
surprise
trust
Sentiments
account_category
Commercial
Fearmonger
HashtagGamer
LeftTroll
NewsFeed
RightTroll

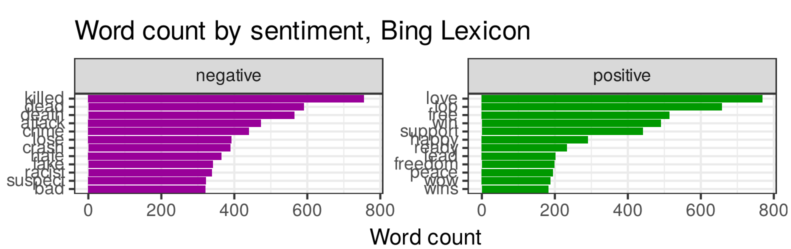

Positivity / Negativity by hundreds of tweets
Score
Commercial
Fearmonger
HashtagGamer
LeftTroll
NewsFeed
RightTroll
0
200
400
600
Tweets (hundreds)

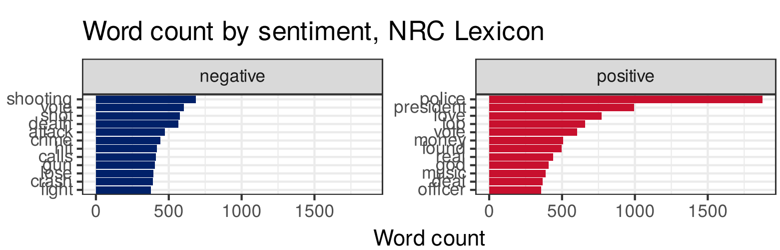
Now we compare the 3 lexicons.

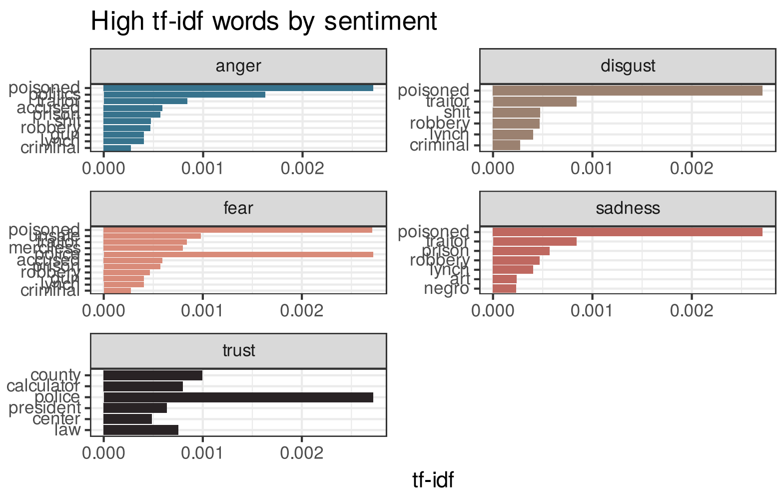



```
# A tibble: 2 × 2
  sentiment     n
  <chr>     <int>
1 negative   3316
2 positive   2308
```

```
# A tibble: 2 × 2
  sentiment     n
  <chr>     <int>
1 negative   4781
2 positive   2005
```







We can observe that NRC is more positive than the other lexicons, even after correcting the issue with Trump being interpreted as a word of “surprise”.

1.4.d LDA Modelling

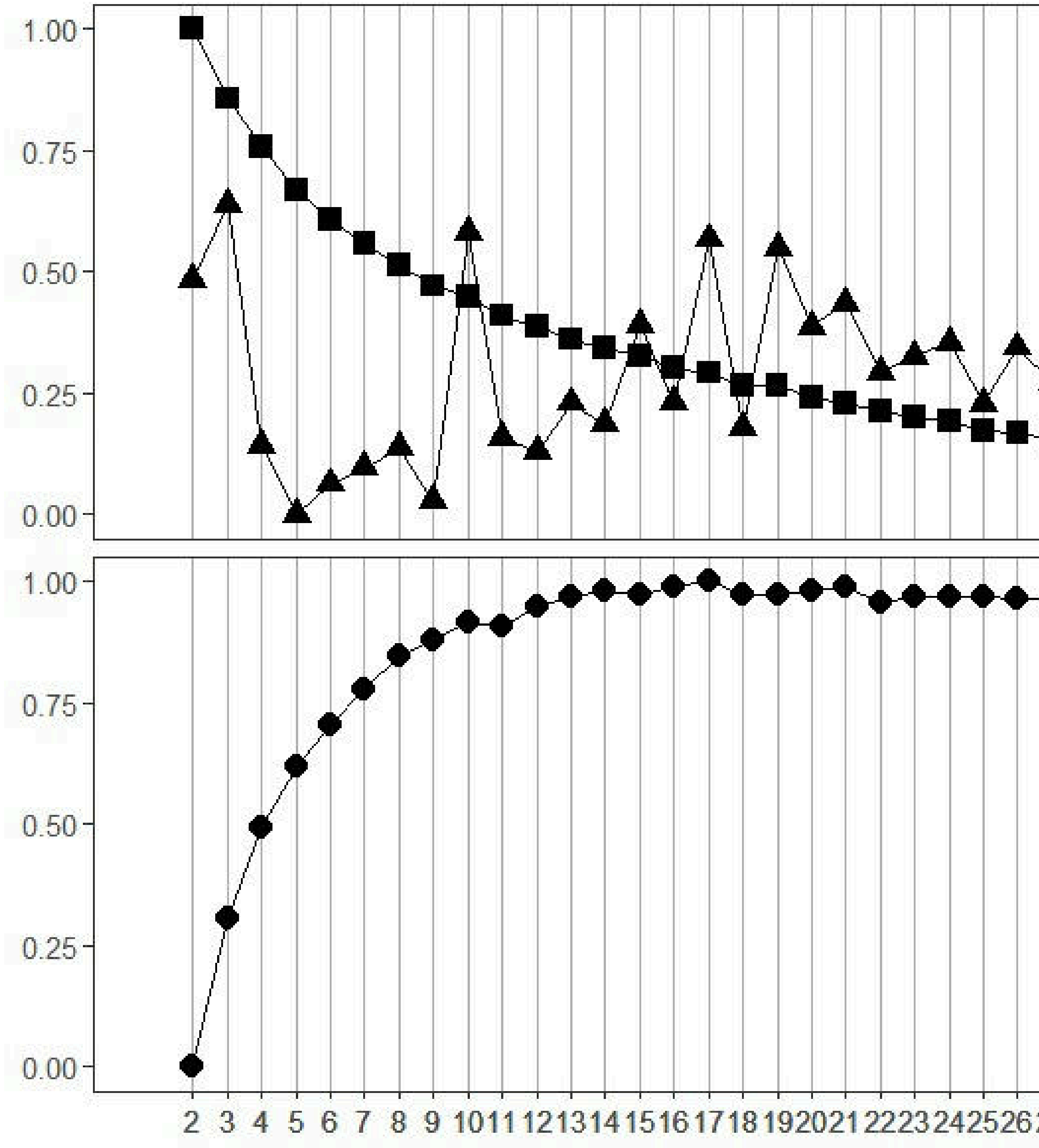
We proceed to use LDA analysis (David M. Blei et al., n.d.) to create a model that splits the tweets we found into topic. We take each tweet as a document and its text as a corpus. The tweets are then aggregated through LDA into topics, which returns us a model for how likely each word is to come out each topic.

We proceed to use LDA analysis to create a model that splits the tweets we found into topic. We take each tweet as a document and its text as a corpus. The tweets are then aggregated through LDA into topics, which returns us a model for how likely each word is to come out each topic.

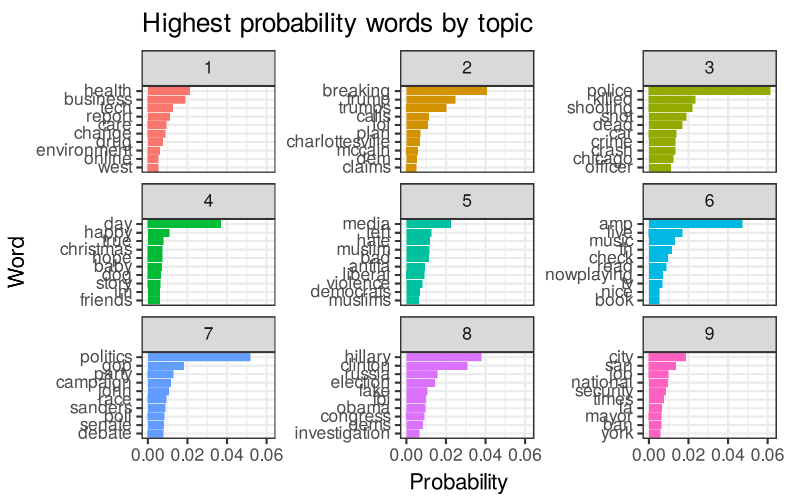
First we have to train the model, so we’re going to divide the tweets into training and testing data with an 80/20 split.

We then run the model for different numbers of topic, and evaluate its accuracy (which is measured by the model’s perplexity). We toggle this codeblock’s execution off because it takes a long time to run, but the model is most accurate with 25 topics (as shown by the plot).

It’s worth noting that perplexity remains high, despite the singular iteration, but that’s to be expected: even in human interpretation it’s recognised that Tweets, by their very nature, are often ambiguous. Astroturf-related tweets, which by their own objective try to be even more ambiguous, are bound to share that quality.


1.00
0.75
0.50
0.25
0.00
1.00
0.75
0.50
0.25
0.00
2 3 4 5 6 7 8 9 10 11 12 13 14 15 16 17 18 19 20 21 22 23 24 25 26

That being said, we can clearly observe patterns of topic forming within the model




```
# A tibble: 248 × 26
   term   topic1 topic2 topic3 topic4 topic5 topic6 topic7 topic8 topic9 topic10
   <chr>   <dbl>  <dbl>  <dbl>  <dbl>  <dbl>  <dbl>  <dbl>  <dbl>  <dbl>   <dbl>
 1 west  0.00538     NA     NA     NA     NA     NA     NA     NA     NA      NA
 2 onli… 0.00542     NA     NA     NA     NA     NA     NA     NA     NA      NA
 3 envi… 0.00618     NA     NA     NA     NA     NA     NA     NA     NA      NA
 4 drug  0.00752     NA     NA     NA     NA     NA     NA     NA     NA      NA
 5 chan… 0.00896     NA     NA     NA     NA     NA     NA     NA     NA      NA
 6 care  0.00936     NA     NA     NA     NA     NA     NA     NA     NA      NA
 7 repo… 0.0111      NA     NA     NA     NA     NA     NA     NA     NA      NA
 8 tech  0.0127      NA     NA     NA     NA     NA     NA     NA     NA      NA
 9 busi… 0.0190      NA     NA     NA     NA     NA     NA     NA     NA      NA
10 heal… 0.0212      NA     NA     NA     NA     NA     NA     NA     NA      NA
# ℹ 238 more rows
# ℹ 15 more variables: topic11 <dbl>, topic12 <dbl>, topic13 <dbl>,
#   topic14 <dbl>, topic15 <dbl>, topic16 <dbl>, topic17 <dbl>, topic18 <dbl>,
#   topic19 <dbl>, topic20 <dbl>, topic21 <dbl>, topic22 <dbl>, topic23 <dbl>,
#   topic24 <dbl>, topic25 <dbl>
```

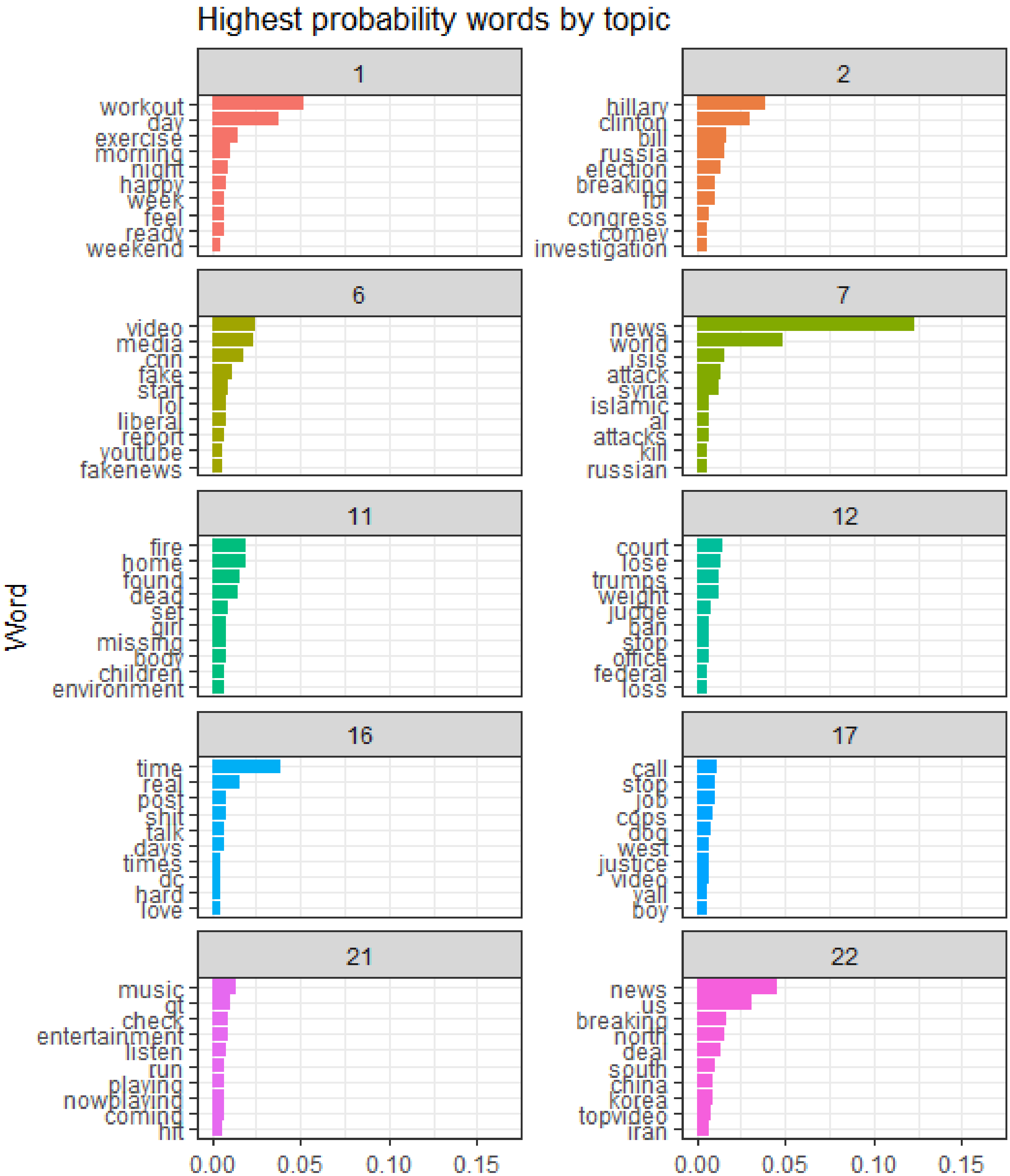
```
# A tibble: 1,756,575 × 3
   document topic  gamma
   <chr>    <int>  <dbl>
 1 1            1 0.0370
 2 2            1 0.0392
 3 3            1 0.0385
 4 4            1 0.0377
 5 5            1 0.0392
 6 6            1 0.0357
 7 7            1 0.0741
```

```
 8 8            1 0.0345
 9 9            1 0.0714
10 10           1 0.0385
# ℹ 1,756,565 more rows
```

```
[1] 9470.8
```

```
[1] 41050.34
```

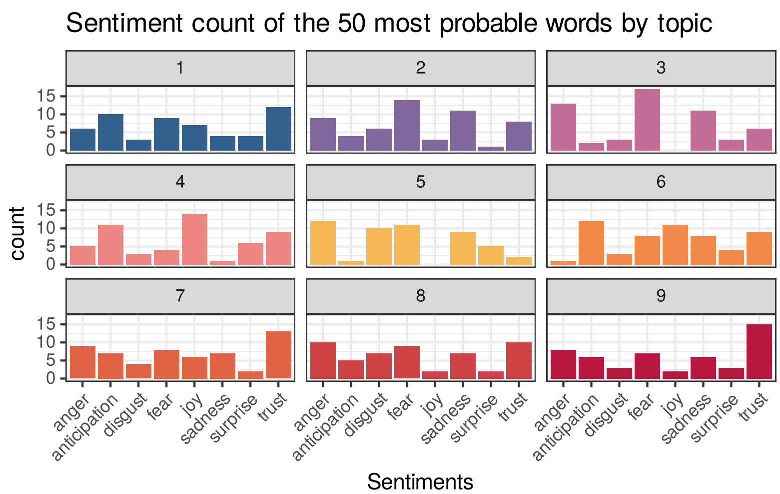
We can observe several clear topic being distinguished, some of which along political lines, like the Obama presidency, Hillary Clinton and Donald Trump. Some of which along cultural topics, like workouts or sports.

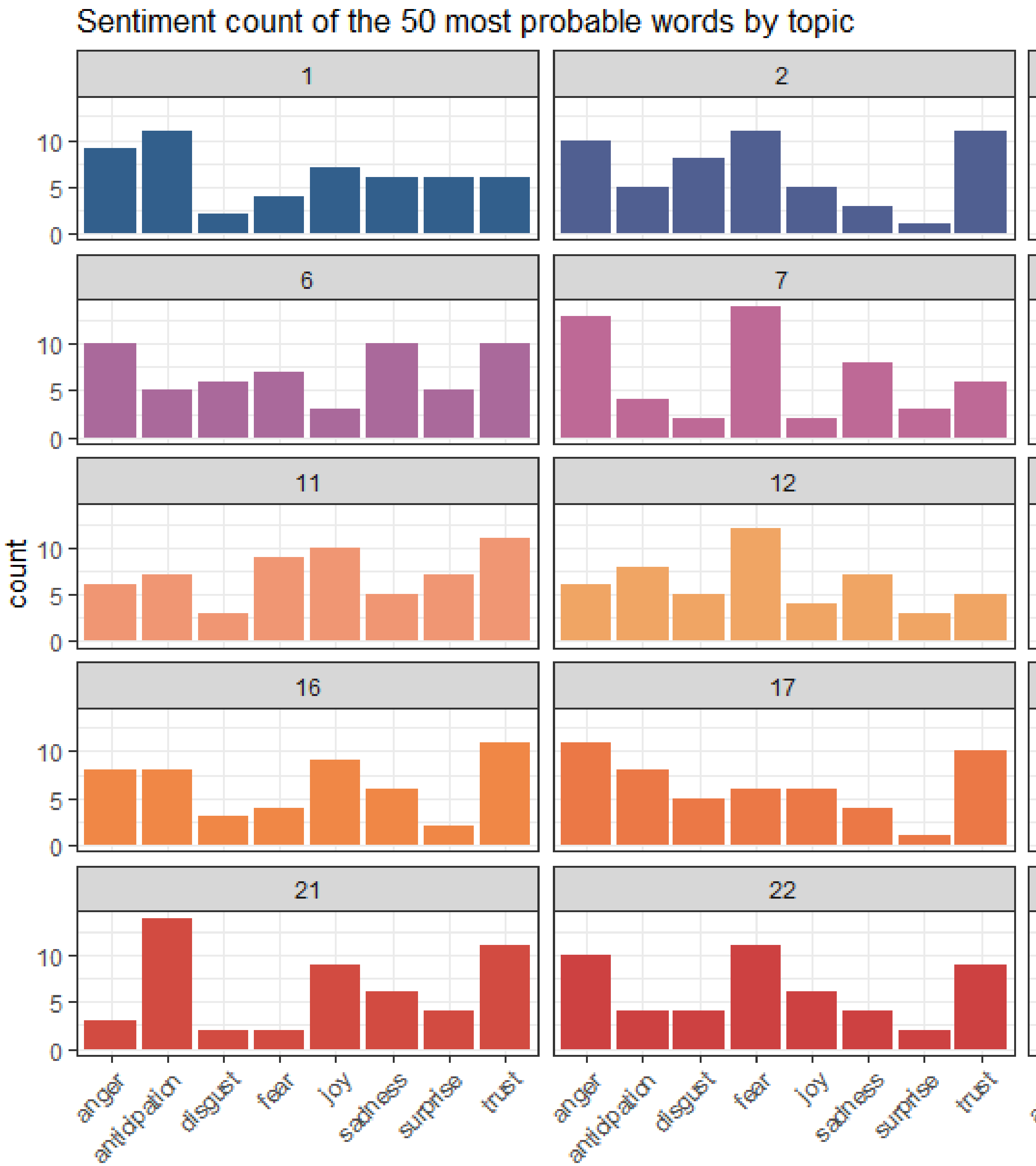

Highest probability words by topic
1
workout
day
exercise
morning
night
happy
week
feel
ready
weekend
2
hillary
clinton
bill
russia
election
breaking
fbi
congress
comey
investigation
6
video
media
cnn
fake
start
lol
liberal
report
youtube
fakenews
7
news
world
isis
attack
syria
islamic
al
attacks
kill
russian
11
fire
home
found
dead
set
girl
missing
body
children
environment
12
court
lose
trumps
weight
judge
ban
stop
office
federal
loss
16
time
real
post
shit
talk
days
times
dc
hard
love
17
call
stop
job
cops
dog
west
justice
video
yall
boy
21
music
gt
check
entertainment
listen
run
playing
nowplaying
coming
hit
22
news
us
breaking
north
deal
south
china
korea
topvideo
iran
Word
0.00
0.05
0.10
0.15
0.00
0.05
0.10
0.15

bl

re

We then evaluate sentiment by topic




Sentiment count of the 50 most probable words by topic
1
2
6
7
11
12
16
17
21
22
count
0
5
10
anger
anticipation
disgust
fear
joy
sadness
surprise
trust

We can observe that topic Trump is correlated with high feelings of trust, hope. This is in stark contrast with the feelings around other political candidates. This is far and away the strongest visible pattern of this analysis, showing clearly the intent behind the operation: through subtle and hard-to-detect political messaging, to associate Trump with hope for the future and positivity, and his opposition with negativity.

Additionally high values of trust and fear oriented words can be observed around multiple topics, but generally fear, trust and anger are the most shared sentiments.

1.5 Conclusion

In this paper we observed that during the 2016 election season, there's clear patterns that we can observe through sentiment analysis that characterize this specific astroturf operation orchestrated by the IRA. Through text analysis, we could observe specific sets of words, through sentiment analysis we could observe the choice in sentiments to be boosted, and through LDA analysis we could observe the distribution of both of these across specific topics. The findings of such tactics were supplemented by the use of more common text-mining approaches like word frequencies and tf-idf.

For example, we noticed that Trump-adjacent topics were commonly associated with positive sentiment, like "trust", and by far right-leaning words and ideas were by far the most shared on our dataset.

From the combination of these analyses and our interpretative work, we can corroborate the assumption that IRA's intention was to aid President-Elect Donald in winning the presidency in 2016. This tracks with the findings of the Mueller report and of most other literature on the subject. What's interesting is the possible application in iterating on these findings to look for consistent patterns across many known astroturf operations, to be finally able to model their occurrence, and finally be able to tackle them before the consequences of their presence become apparent, as has been the case so far.

1.6 Future Work

1.6.a Network Analysis

It's opportune to verify the hypothesis that astroturf operations such as this one have effects on polarization, observed through network betweenness. We hope to do so by checking for differences between data gathered before and after the election

1.6.b New data

It'd be interesting to observe the evolution of astroturf given the recent developments in generative technology. To do so, we'd need to access new, large amounts of data. This cna't cheaply be done off of Twitter (now X), so we hope to do so through fediverse or bluseky (or AT-based) platforms.

With this new data, we could then run a similar kind of analysis to observe if the patterns we found in 2016 remain and fully develop a recognisation model. At the same time, we could better develop a model using the help of network analysis: shoudl our hypothesis about polarization hold, increases in network polarization would be possible markers of astroturf campaigns, and therefore “hot spots” to analyse.

1.6.c LDA opportunities

Due to computational constraints on the datasets of such a size, we were able to run LDA with only one iteration, leading to fairly significant results. This leaves us optimistic on the possible results that could be achieved by running the algorithm with at least 1000 iterations, potentially optimizing astroturf recognition and detection.

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