INSY 5378 DATA SCIENCE PROGRAMMING APPROACH

GROUP 7

Social Media Analytics

Team Members:

Salman Mohammed-1001398053	salman.mohammed@mavs.uta.edu	Information Systems
Sujatha Sivakumar-1001359237	sujatha.sivakumar@mavs.uta.edu	Information Systems
Tapan Patel-1001450804	tapansaileshbha.patel@mavs.uta.edu	Information Systems

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INTRODUCTION

Donald J. Trump became the 45th President of the United States on January 20, 2017. Since the inauguration, President Trump is actively initiating new policies and conversations, which generate active conversations in the social media.

In this project we collected all such generated traffic related to President Trump from twitter and performed social media analytics to understand the opinion among the people regarding the president.

TWITTER STREAMING

We have used twitter streaming API to collect tweets from twitter. Using the credentials obtained from the API we have used Tweepy module to collect real time tweets from all over the USA using hash tags like trump , Donald trump, POTUS. We collected 10,000 such tweets.

We have also collected demographic specific tweets using geo location co-ordinates for five different states- California, Michigan, Kansas, Texas, Pennsylvania. We collected 1000 tweets from each location.

PRE-PROCESSING

We extracted the tweets text from the raw JSON format obtained from the streaming API and cleansed the text to separate URLs, punctuations, digits, emoticons and Unicode using HTMLParser, Preprocessor, RegEx modules. The preprocessed text was then stemmed and lemmatized using Lancaster stemming. The Stemmed text was then cleansed of stop words using the NLTK module. Also, special words such as “Trump”, “Donald” etc. were removed from the text.

SENTIMENT ANALYSIS

We analyzed the sentiments of each tweet to calculate the subjectivity and polarity scores of the tweets. Here subjectivity means that there is a context in the text. High subjectivity scores mean that the tweets have proper context. Polarity on the other hand portrays the nature of the content. The value varies from -1 to +1 where minus values indicate that the tweets are negative and positive values indicate that the tweets are positive.

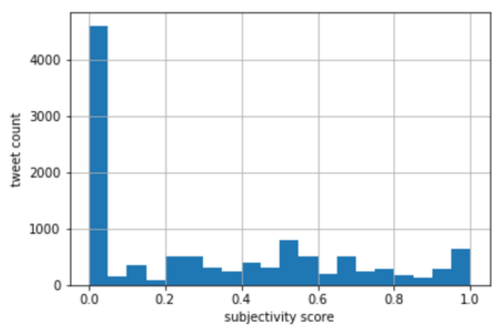
We used text blob to calculate the average subjectivity and polarity scores. For the tweet corpus. The same was repeated for the demographics specific tweets.

Location	Subjectivity	Polarity
General	0.314812491	0.037036686
California	0.27546413	0.014630198
Michigan	0.350845469	0.043771025
Kansas	0.317810504	0.029519824
Texas	0.315490073	0.02795444
Pennsylvania	0.307148603	0.031986073

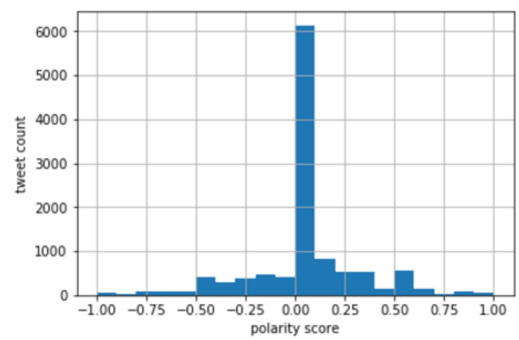
The Graphs are as follows:

Trump General:

Subjectivity:

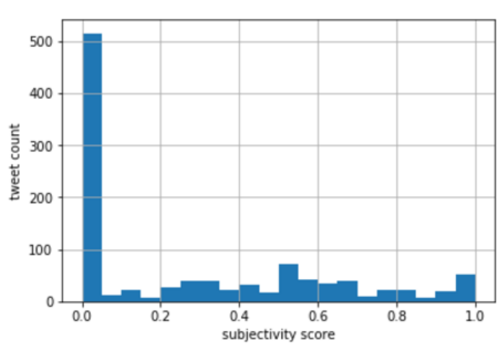


Polarity:

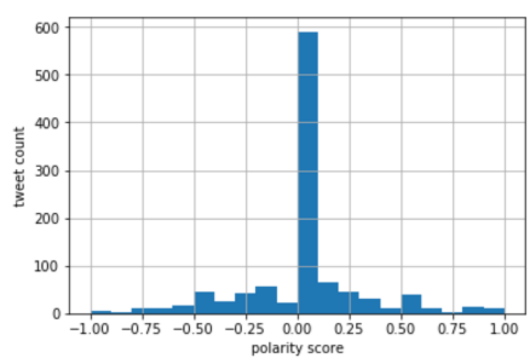


California:

Subjectivity:

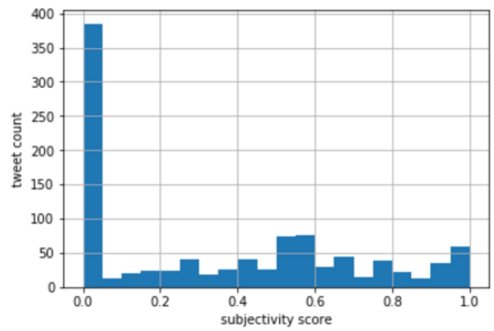


Polarity:

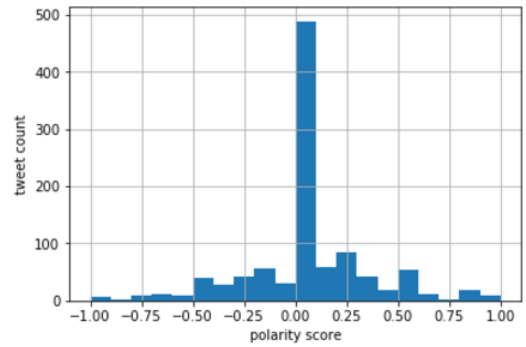


Michigan:

Subjectivity:

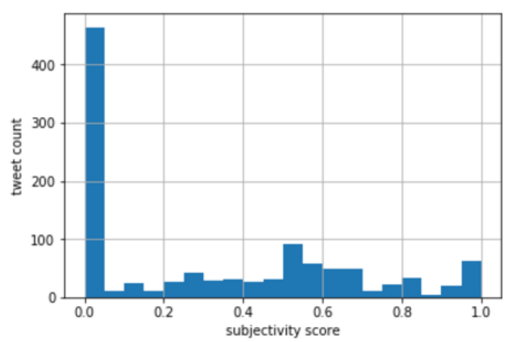


Polarity:

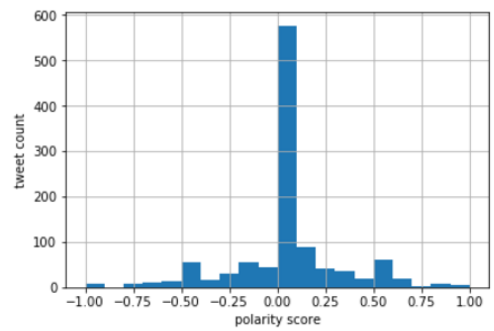


Kansas:

Subjectivity:

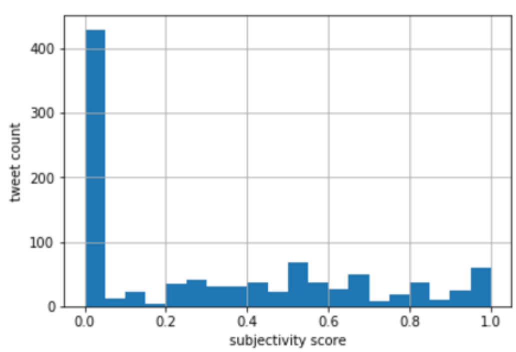


Polarity:

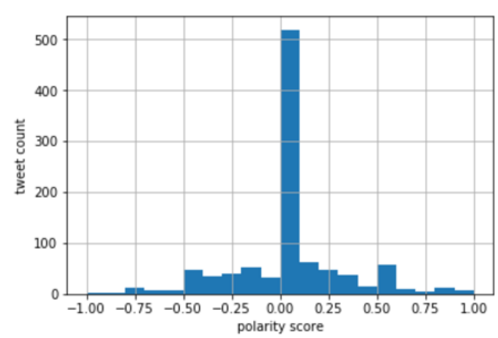


Texas:

Subjectivity:

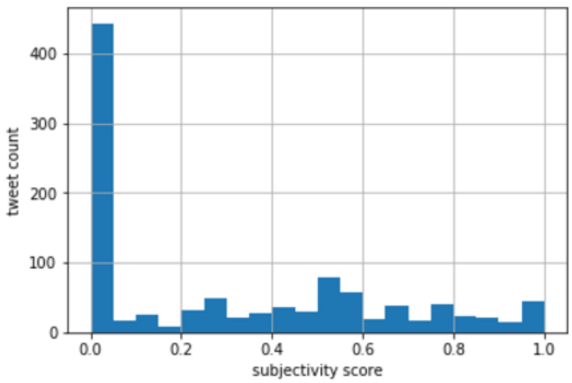


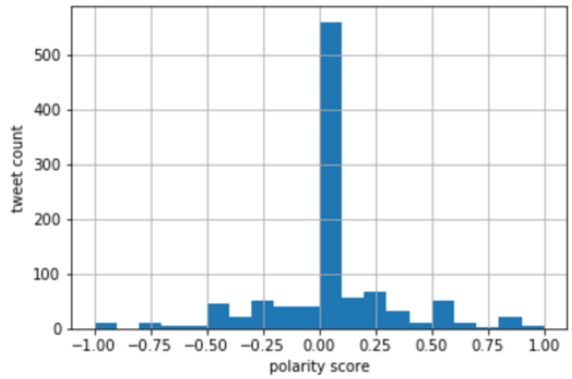
Polarity:



Pennsylvania:

Subjectivity: **Polarity:**



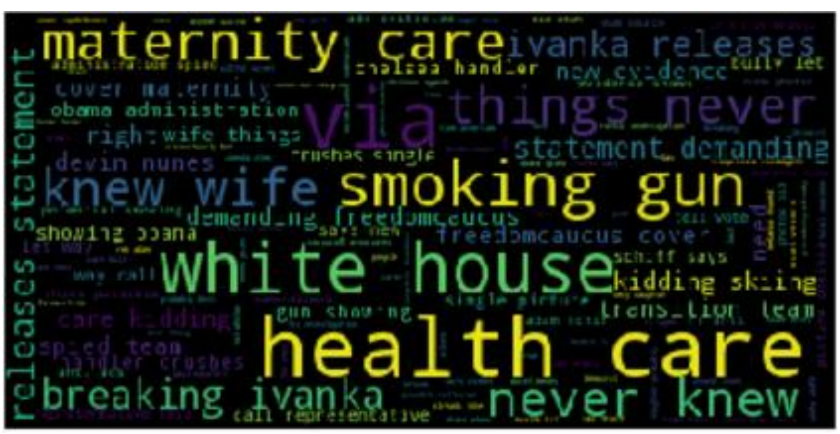


From the above results, we find that there is maximum subjectivity and polarity score in Michigan. This means that people are really being positive about the new president in Michigan. On a general note, we find there is mostly positive comments about the president.

Word Cloud Generation

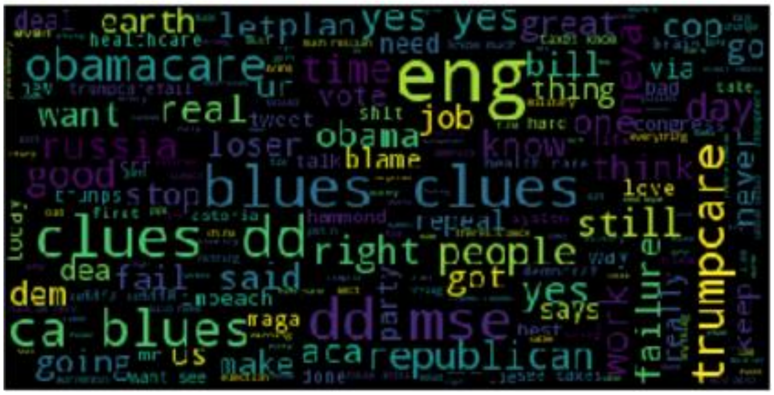
We generated a word cloud from the cleansed text using word cloud module to find out the most common words used in the tweets about the president with the data from all over the USA as well as from different states.

General



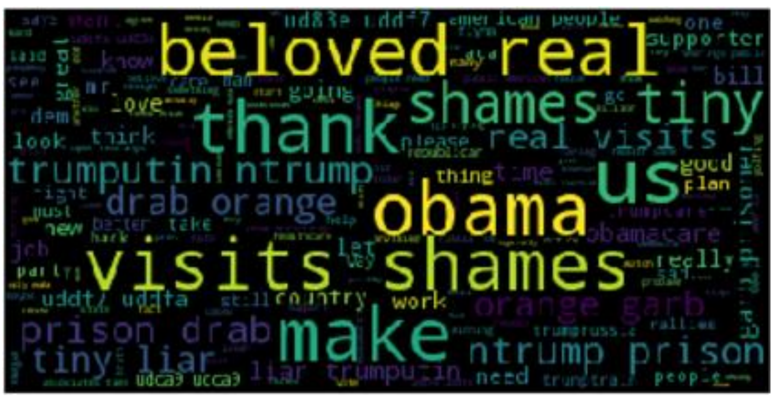
From the figure we can see that the most used words were Maternity care, Smoking Gun, White House, Health Care and about the president’s family.

California



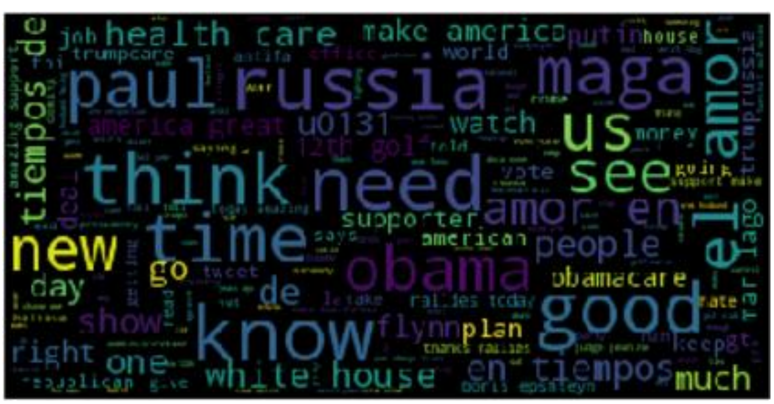
From the figure we can see that the most used words were trump care, Obama care.

Michigan



From the figure we can see that the most used words were Obama, visits, shames, beloved.

Kansas

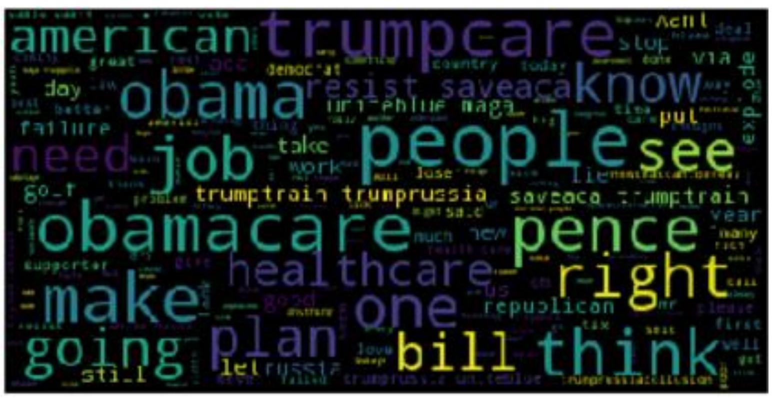


From the figure we can see that the most used words were Russia, Obama care, paul.

Texas

From the figure we can see that the most used words were Obama care, supporter, America, Obama.

Pennsylvania



From the figure we can see that the most used words were job, bill, trump care, Obama care, republican.

TOPIC MODELLING

From the cleansed text and word cloud we created two models for analyzing the trending topics in the tweets. We used two machine learning algorithms to do this - the Non- Negative Matrix Factorization & Latent Dirilect Allocation. The results are as follows.

General:

NMF:

[4432 4504 5079 2923 3811 2293 1762]
russia
says
team
like
people
health
evidence
[3603 4504 5079 2923 2293 3811 1762]
obama
says
team
like
health
people
evidence
[774 3811 1762 756 5175 6084 656]
care
people
evidence
campaign
time
white
breaking
[2397 5079 1762 756 5175 656 6084]
house
team
evidence
campaign
time
breaking
white
[3409 1762 756 5175 6084 656 1878]
new
evidence
campaign
time
white
breaking
fbi
[5974 4504 2923 5079 2293 3811 2616]
vote
says
like
team
health
people
investigation
[3573 4504 5079 2293 3811 1762 2616]
nunes
says
team
health
people
evidence
investigation
/**//**//**//**//**//**//**//**//**//**/
(94911, 6228)
5 281.1761014031083
10 277.63825384985944
15 274.8344958639479
20 272.45733636863696
25 270.255435173741

LDA:

Topic #1 (0, '0.021*"nunes" + 0.017*"voters" + 0.017*"utah" + 0.016*"health" + 0.013*"trumprussia" + 0.011*"us" + 0.010*"things" + 0.009*"breaking" + 0.009*"cnn" + 0.009*"bid"')
Topic #2 (1, '0.032*"russia" + 0.020*"says" + 0.018*"new" + 0.017*"via" + 0.016*"evidence" + 0.013*"would" + 0.013*"bill" + 0.012*"putin" + 0.010*"russian" + 0.009*"know"')
Topic #3 (2, '0.032*"obama" + 0.025*"care" + 0.022*"house" + 0.016*"investigation" + 0.015*"photos" + 0.015*"ads" + 0.012*"right" + 0.011*"criticize" + 0.010*"surveillance" + 0.009*"knew"')
Topic #4 (3, '0.020*"anti" + 0.017*"like" + 0.016*"people" + 0.016*"melania" + 0.013*"never" + 0.012*"said" + 0.011*"de" + 0.010*"best" + 0.010*"call" + 0.008*"way"')
Topic #5 (4, '0.018*"vote" + 0.016*"team" + 0.016*"rt" + 0.016*"news" + 0.014*"campaign" + 0.014*"time" + 0.013*"fbi" + 0.013*"get" + 0.011*"white" + 0.011*"see"')

California:

NMF:

[244 555 967 317 329 328 327]
eng
neva
yuge
gets
gonzaga
gonna
gone
[964 920 377 127 550 575 608]
yes
want
house
care
need
obamacare
people
[196 163 818 967 328 327 326]
dd
cop
today
yuge
gonna
gone
golfing
[103 358 842 722 807 688 558]
blues
healthcare
trumps
says
thing
republicans
news

[144 555 672 209 597 806 321]
clues
neva
real
dems
party
theresistance
gives
[121 705 127 608 833 864 193]
ca
russia
care
people
trumpcare
ud83e
day
[540 575 440 815 864 713 946]
mse
obamacare
know
time
ud83e
said
work
/**//**//**//**//**//**//**//**//**/
(7028, 968)
5 65.6886597201659
10 63.749510022670194
15 62.57795348375914
20 61.58733663996545
25 60.76183289876763

LDA:

Topic #1 (0, '0.031*"yes" + 0.016*"good" + 0.013*"want" + 0.011*"repeal" + 0.011*"dems" + 0.010*"healthcare" + 0.009*"mr" + 0.009*"right" + 0.008*"congress" + 0.008*"money"')
Topic #2 (1, '0.070*"eng" + 0.031*"trumpcare" + 0.016*"dd" + 0.013*"russia" + 0.013*"fail" + 0.013*"obama" + 0.010*"job" + 0.010*"plan" + 0.009*"deal" + 0.009*"take"')
Topic #3 (2, '0.020*"obamacare" + 0.019*"know" + 0.016*"ca" + 0.014*"clues" + 0.010*"got" + 0.009*"blues" + 0.008*"failure" + 0.008*"real" + 0.007*"think" + 0.007*"health"')
Topic #4 (3, '0.038*"get" + 0.029*"like" + 0.027*"people" + 0.017*"bill" + 0.017*"mse" + 0.016*"neva" + 0.013*"care" + 0.011*"let" + 0.011*"house" + 0.010*"world"')
Topic #5 (4, '0.014*"ude06" + 0.012*"time" + 0.011*"would" + 0.010*"work" + 0.008*"stop" + 0.007*"says" + 0.007*"day" + 0.007*"make" + 0.007*"office" + 0.007*"ur"')

Michigan:

NMF:

[671 631 603 959 830 1014 330]
people
obama
need
trumputin
shames
visits
garb
[748 631 649 603 929 234 72]
real
obama
orange
need
tiny
drab
beloved
[477 631 625 649 929 72 234]
know
obama
ntrump
orange
tiny
beloved
drab
[509 631 929 72 234 1014 718]
like
obama
tiny
beloved
drab
visits
prisoner
[500 603 234 929 959 72 718]
liar
need
drab
tiny
trumputin
beloved
prisoner
[981 631 929 330 718 72 540]
ud83e
obama
tiny
garb
prisoner
beloved
maga
[717 625 649 603 1014 959 234]
prison
ntrump
orange
need
visits
trumputin
drab
/**//**//**//**//**//**//**//**//**//**/
(7901, 1086)
5 71.1969100461767
10 69.89277515270108
15 68.68042059592737
20 67.49074063475594
25 66.43041861139926

LDA:

Topic #1 (0, '0.022*"ntrump" + 0.021*"orange" + 0.021*"american" + 0.014*"care" + 0.010*"even" + 0.010*"go" + 0.009*"want" + 0.009*"repeal" + 0.009*"pres" + 0.009*"sad"')
Topic #2 (1, '0.031*"people" + 0.028*"know" + 0.021*"liar" + 0.016*"like" + 0.015*"job" + 0.015*"great" + 0.014*"ties" + 0.014*"bill" + 0.013*"obamacare" + 0.012*"would"')
Topic #3 (2, '0.023*"real" + 0.017*"russia" + 0.016*"us" + 0.015*"get" + 0.014*"drab" + 0.013*"shames" + 0.013*"visits" + 0.013*"tiny" + 0.012*"really" + 0.012*"garb"')
Topic #4 (3, '0.022*"prison" + 0.014*"one" + 0.013*"work" + 0.013*"time" + 0.012*"trumpcare" + 0.010*"still" + 0.009*"golfing" + 0.008*"today" + 0.008*"big" + 0.008*"course"')
Topic #5 (4, '0.018*"need" + 0.013*"obama" + 0.011*"maga" + 0.010*"let" + 0.009*"open" + 0.008*"public" + 0.008*"associates" + 0.008*"think" + 0.007*"hearings" + 0.007*"man"')

Kansas:

NMF:

[684 713 870 549 836 1219 1430]
like
maga
paul
house
obamacare
time
white
[487 367 713 549 717 836 1219]
golf
en
maga
house
make
obamacare
time
[835 367 713 870 1219 717 836]
obama
en
maga
paul
time
make
obamacare
[490 870 713 1219 359 809   70]
good
paul
maga
time
el
news
america
[1036 713 870 359 519 1430   70]
russia
maga
paul
el
health
white
america
[636 367 870 359 809 808 1400]
know
en
paul
el
news
new
voted
[880 1205 367 717 549 1219 809]
people
think
en
make
house
time
news
/**//**//**//**//**//**//**//**//**//**/
(9332, 1471)
5 80.21845174450405
10 79.28429881508596
15 78.39643003656813
20 77.60154768408847
25 76.85701134407385

LDA:

Topic #1 (0, '0.016*"tiempos" + 0.015*"amor" + 0.011*"obamacare" + 0.010*"health" + 0.009*"make" + 0.007*"people" + 0.007*"putin" + 0.006*"show" + 0.005*"u2705trump" + 0.005*"man"')
Topic #2 (1, '0.031*"de" + 0.009*"news" + 0.009*"voted" + 0.008*"la" + 0.007*"new" + 0.007*"antifa" + 0.007*"rallies" + 0.007*"world" + 0.006*"let" + 0.006*"boris"')
Topic #3 (2, '0.017*"obama" + 0.016*"golf" + 0.012*"america" + 0.011*"watch" + 0.011*"would" + 0.011*"deal" + 0.011*"bill" + 0.010*"supporters" + 0.010*"healthcare" + 0.008*"tv"')
Topic #4 (3, '0.032*"en" + 0.031*"el" + 0.016*"like" + 0.016*"us" + 0.013*"get" + 0.013*"care" + 0.013*"one" + 0.012*"u0131" + 0.010*"tweets" + 0.010*"white"')
Topic #5 (4, '0.016*"russia" + 0.015*"maga" + 0.013*"house" + 0.010*"epshteyn" + 0.009*"said" + 0.009*"cia" + 0.008*"think" + 0.008*"war" + 0.008*"husband" + 0.007*"says"')

Texas:

NMF:

[546 648 511 588 380 539 1042]
like
news
know
man
golf
let
ude4f
[712 588 948 380 956 583 379]
people
man
think
golf
time
magamarch
going
[677 648 511 708 1042 539 983]
obamacare
news
know
paul
ude4f
let
trumpcare
[676 588 380 948 917 379 583]
obama
man
golf
think
supporters
going
magamarch

[153 648 708 1042 379 1084 585]
care
news
paul
ude4f
going
watch
make
[54 588 917 583 1084 1023 390]
america
man
supporters
magamarch
watch
ud83e
great
[834 642 588 648 539 708 917]
says
need
man
news
let
paul
supporters
/**//**//**//**//**//**//**//**//**//**/
(7467, 1136)
5 68.3885955409885
10 67.34240867838243
15 66.46803765166341
20 65.6734352051827
25 64.9230317028779

LDA:

Topic #1 (0, '0.024*"us" + 0.016*"would" + 0.016*"insurance" + 0.011*"know" + 0.011*"ur" + 0.010*"jeanine" + 0.010*"paul" + 0.010*"well" + 0.010*"stop" + 0.010*"work"')
Topic #2 (1, '0.033*"like" + 0.015*"america" + 0.013*"going" + 0.011*"good" + 0.011*"want" + 0.010*"back" + 0.010*"nothing" + 0.010*"see" + 0.009*"let" + 0.008*"show"')
Topic #3 (2, '0.018*"care" + 0.017*"says" + 0.015*"obamacare" + 0.012*"keep" + 0.010*"bannon" + 0.009*"could" + 0.009*"health" + 0.008*"read" + 0.008*"much" + 0.008*"stand"')
Topic #4 (3, '0.032*"people" + 0.031*"get" + 0.018*"need" + 0.013*"trumpcare" + 0.011*"thanks" + 0.011*"believe" + 0.011*"via" + 0.010*"still" + 0.010*"anti" + 0.009*"bill"')
Topic #5 (4, '0.014*"news" + 0.014*"one" + 0.014*"obama" + 0.013*"supporters" + 0.012*"watch" + 0.008*"pence" + 0.008*"needs" + 0.008*"golf" + 0.007*"love" + 0.007*"right"')

Pennsylvania:

NMF:

[787 1112 752 473 162 918 1074]
people
trumpcare
obama
healthcare
care
right
think
[753 1112 752 473 918 1121 1074]
obamacare
trumpcare
obama
healthcare
right
trumptrain
think
[627 162 435 57 801 1238 1086]
like
care
going
america
plan
work
today
[1118 918 1074 435 1238 1086 472]
trumprussia
right
think
going
work
today
health

[786 752 473 918 57 1086 1171]
pence
obama
healthcare
right
america
today
uniteblue
[665 162 435 1054 57 670 1086]
maga
care
going
tax
america
make
today
[904 1112 162 1074 1121 435 943]
resist
trumpcare
care
think
trumptrain
going
saveaca
/**//**//**//**//**//**//**//**//**//**/
(8178, 1262)
5 73.47788783198567
10 72.311824761006
15 71.30217390740431
20 70.42016784677571
25 69.62758089075112

LDA:

Topic #1 (0, '0.034*"trumprussia" + 0.024*"take" + 0.022*"u2019" + 0.020*"obama" + 0.017*"one" + 0.014*"health" + 0.014*"could" + 0.014*"american" + 0.014*"best" + 0.014*"fbi"')
Topic #2 (1, '0.020*"trumprussiacollusion" + 0.019*"voters" + 0.013*"man" + 0.013*"people" + 0.012*"democrats" + 0.011*"employer" + 0.011*"get" + 0.011*"future" + 0.010*"another" + 0.010*"loser"')
Topic #3 (2, '0.029*"trumpcare" + 0.022*"obamacare" + 0.020*"away" + 0.020*"war" + 0.019*"bernie" + 0.012*"something" + 0.012*"government" + 0.012*"maybe" + 0.011*"tweets" + 0.011*"ahca"')
Topic #4 (3, '0.034*"via" + 0.022*"going" + 0.019*"plan" + 0.018*"well" + 0.016*"daily" + 0.015*"disenchanted" + 0.015*"aged" + 0.015*"newsletter" + 0.013*"would" + 0.012*"us"')
Topic #5 (4, '0.048*"like" + 0.030*"guy" + 0.021*"message" + 0.013*"said" + 0.012*"look" + 0.011*"golfing" + 0.011*"spicer" + 0.010*"human" + 0.010*"soros" + 0.010*"worst"')

INSIGHTS

From the sentiment analysis we find that over all there is a positive attitude about the president. However, in states like California the negative sentiments are more predominant while in republican states like Texas the sentiments are more positive and are in favor of the president.

From the word cloud, we find that the topic most tweeted about was health care and the Russian issue all over the US. However, to be more specific Pennsylvania speaks more about Russia rather than health care.

From the topics we obtained from topic modeling the most trending topics are about Healthcare. Despite the geographic location, Health Care is trending because president Trump is planning to abolish the ObamaCare plan and rebuild it as TrumpCare with more additions to it. This discussion has been subjected to massive criticism all over the United States and people have taken to social media to express their views.