Expression of Depression

A comparison of depression-related text across social media platforms

Presented by LEAST SQUARES

Agenda

① Background & Project Objective

② Social Media Platform Deep Dives

③ Social Media Platform Comparisons

④ Conclusions & Next Steps

Part 1

Background & Project Objectives

Background

- People suffering from various mental health illnesses often turn to social media for support and resources.

- It is often difficult to identify depression, so organizations are looking for new ways to find and reach out to those suffering with depression.

- It can be insightful to understand how depressed users interact with different social media websites, since behavior varies greatly among these outlets.

Text Associated with Depression

- First-person singular pronouns - increased use of I *(Rude et al., 2004)*
- Absolutist words - ex. always, totally, entire, must, have to, never, etc. *(Al-Mosaiwi & Johnstone 2018)*
- Negative sentiment and general sadness *(Tausczik & Pennebaker, 2009 & De Choudhury et al., 2013)*
- Anxiety *(Coppersmith et al., 2014)*
- Anger *(Coppersmith et al., 2014)*
- Swearing *(Resnik et al., 2015)*
- Death interest *(Coppersmith et al., 2015)*
- Key life domains such as work or school *(De Choudhury et al., 2013)*
- Expression of medical concern and religious involvement *(De Choudhury et al., 2013)*

Project Objectives

- Gain insight into how depression is expressed and discussed across social media and forums

- Explore similarities and differences of the expression of depression across each platform and relate these findings to previous research

- With this information, we hope that public health organizations and mental health advocacy groups can better target their outreach to support depressed individuals

Methodology

twitter
rtweet package

Depressed Sample: 169,472 Tweets containing the word ‘depressed’
Random Sample: 71,896 Most recent tweets

reddit
RedditExtractoR

Depressed Sample: 385 Posts and 2197 Comments from depression-related subreddits
Random Sample: Unable to pull, so used eRisk (CLEF) data (below)

tumblr.
Screen Scraping & tumblR

Depressed Sample: 1607: #depressed, 2497: #depression, 4218: #depressing, 4290: #depressive, 2192: #sad
Random Sample: 1512 trending posts

Blog & Forum
Screen Scraping

Depressed Sample: 34,307 posts from thread in depressed forum in Beyond Blue and Psychcentral
Random Sample: 113,469 Posts from general discussion threads in Straight Dope

Early Risk Detection (CLEF): Data from eRisk Lab

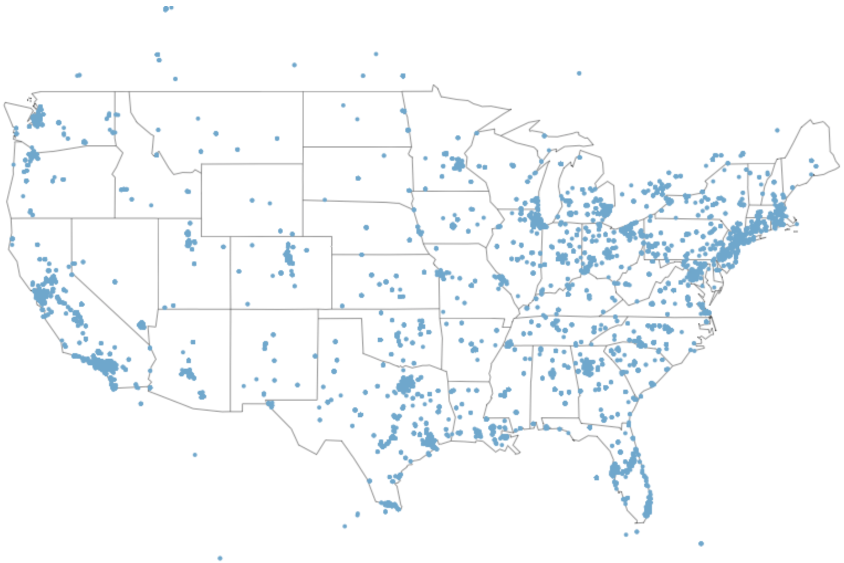
Labeled reddit data (45,241 depressed user posts and 334,764 non-depressed user posts) from 2017

Part 2

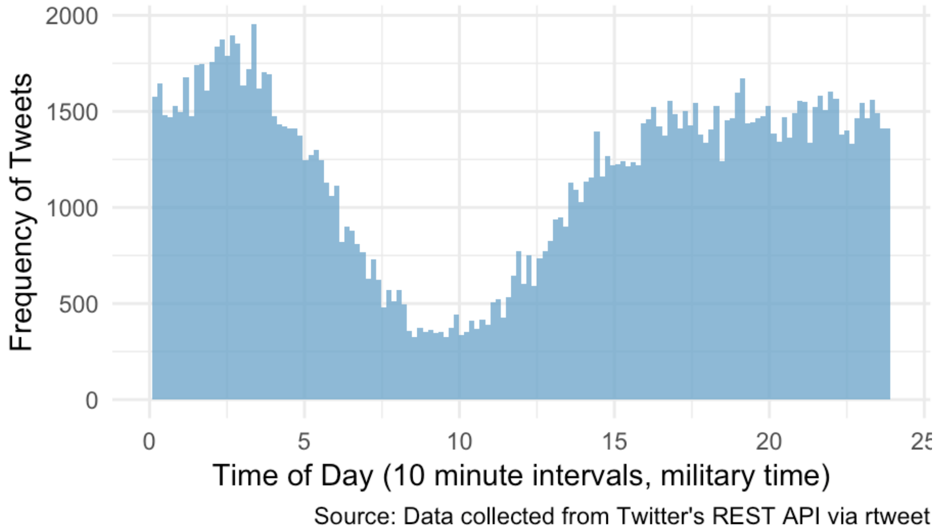
Social Media Platform Deep Dives

Twitter - WHERE & WHEN

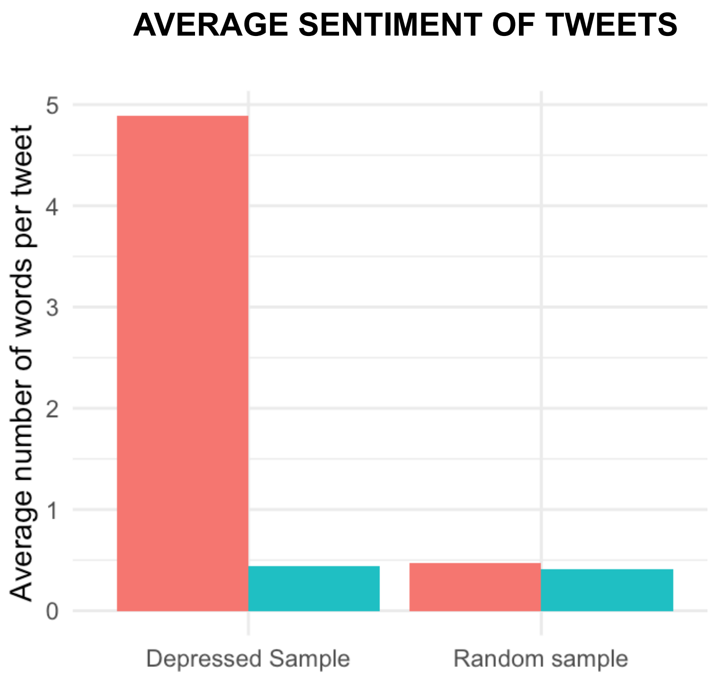
'DEPRESSED' GEOLOCATIONS

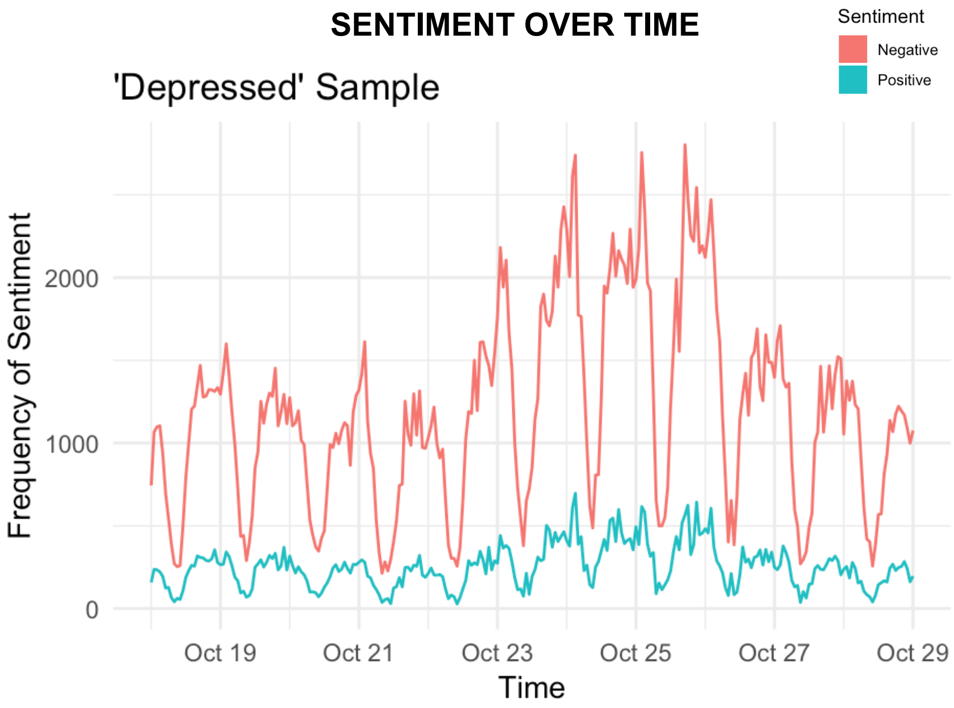


FREQUENCY OF 'DEPRESSED' TWEETS BY THE HOUR

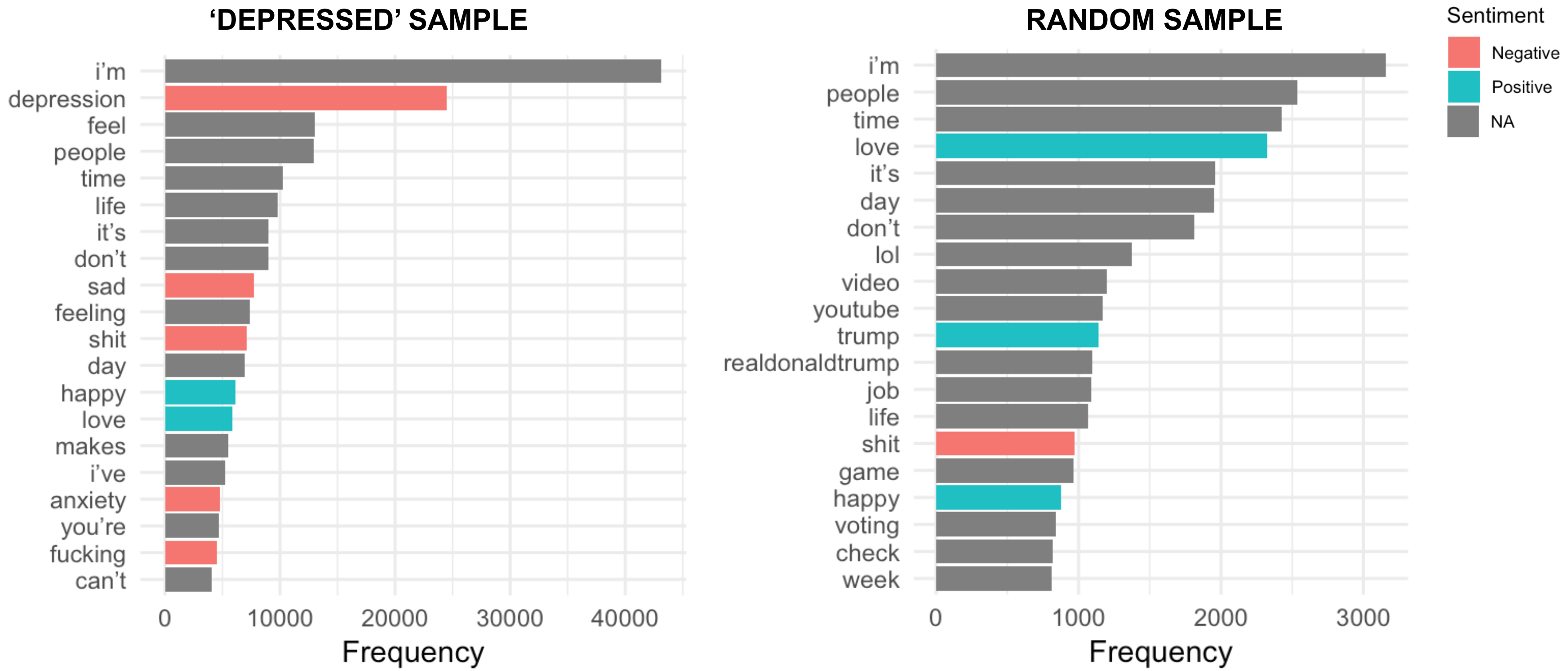


Twitter - SENTIMENT ANALYSIS





Twitter - SENTIMENT ANALYSIS

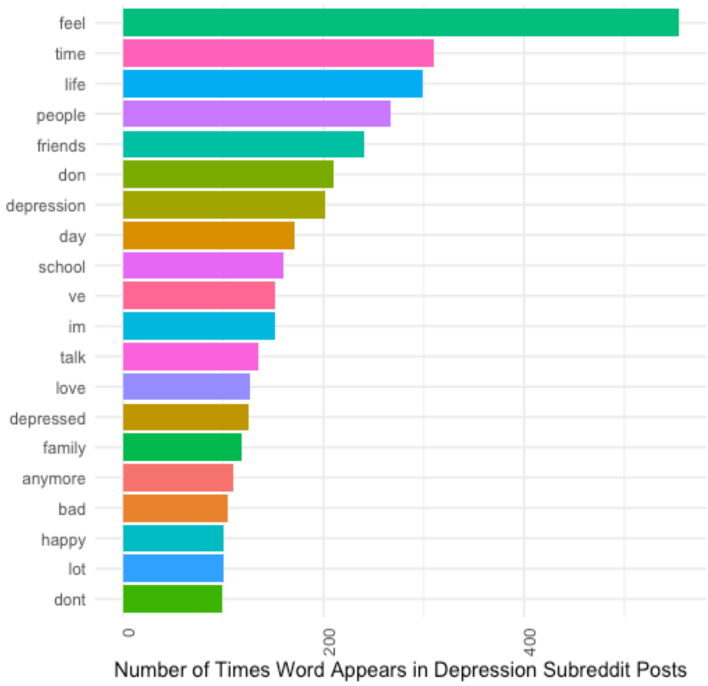


Twitter Summary

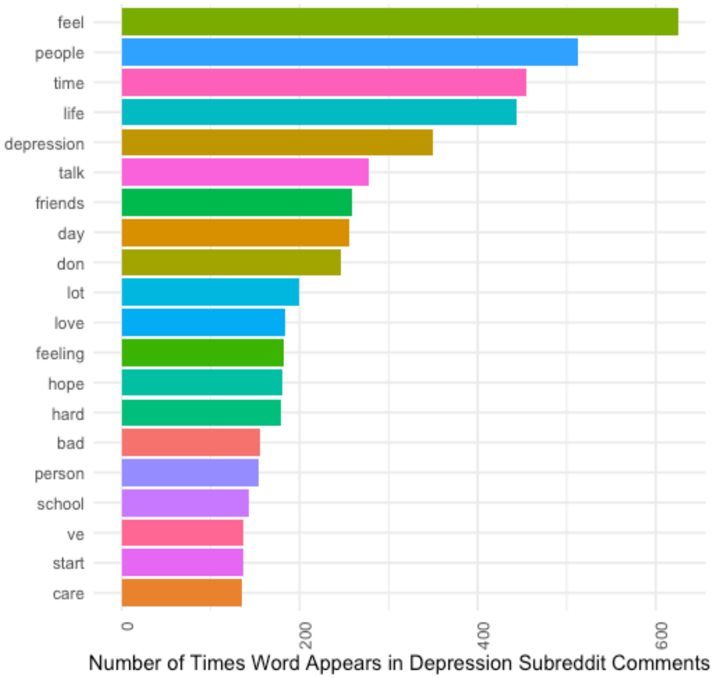
Mirrors previous research on text and depressions: Increased use of first person singular pronouns, negative sentiment, absolutist words, swearing

Reddit - FREQUENT WORDS

POSTS



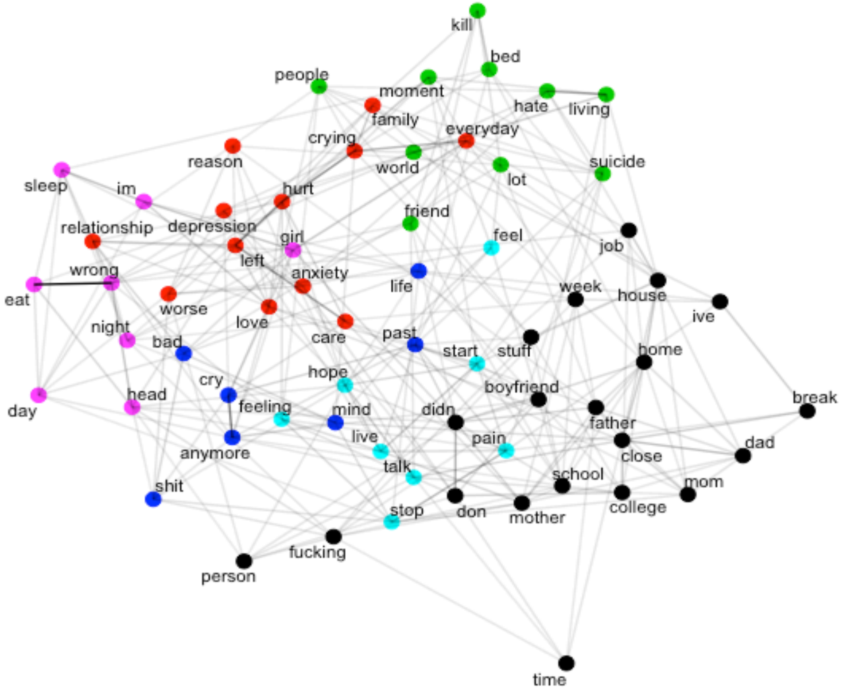
COMMENTS



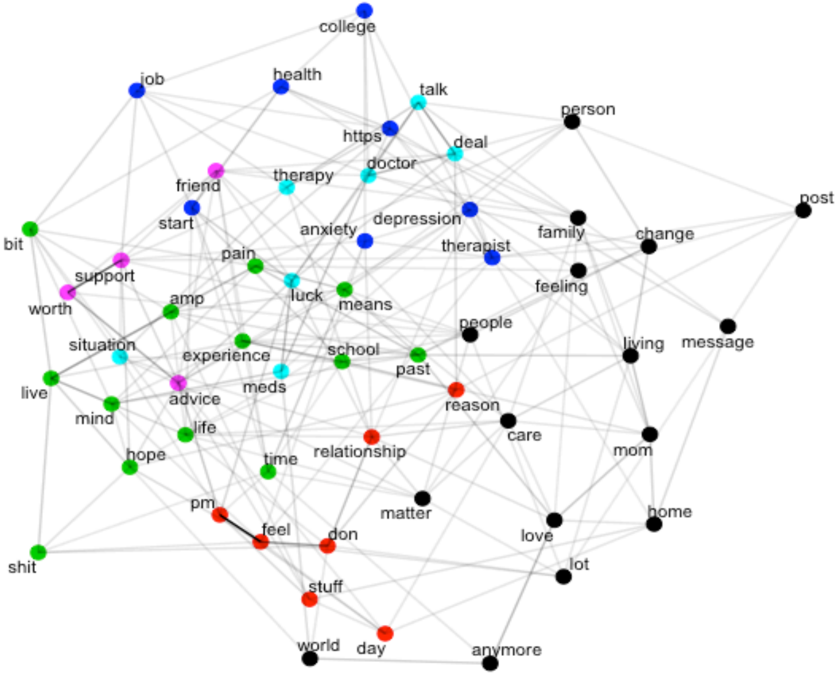
Reddit - NETWORK ANALYSIS

reddit

POSTS



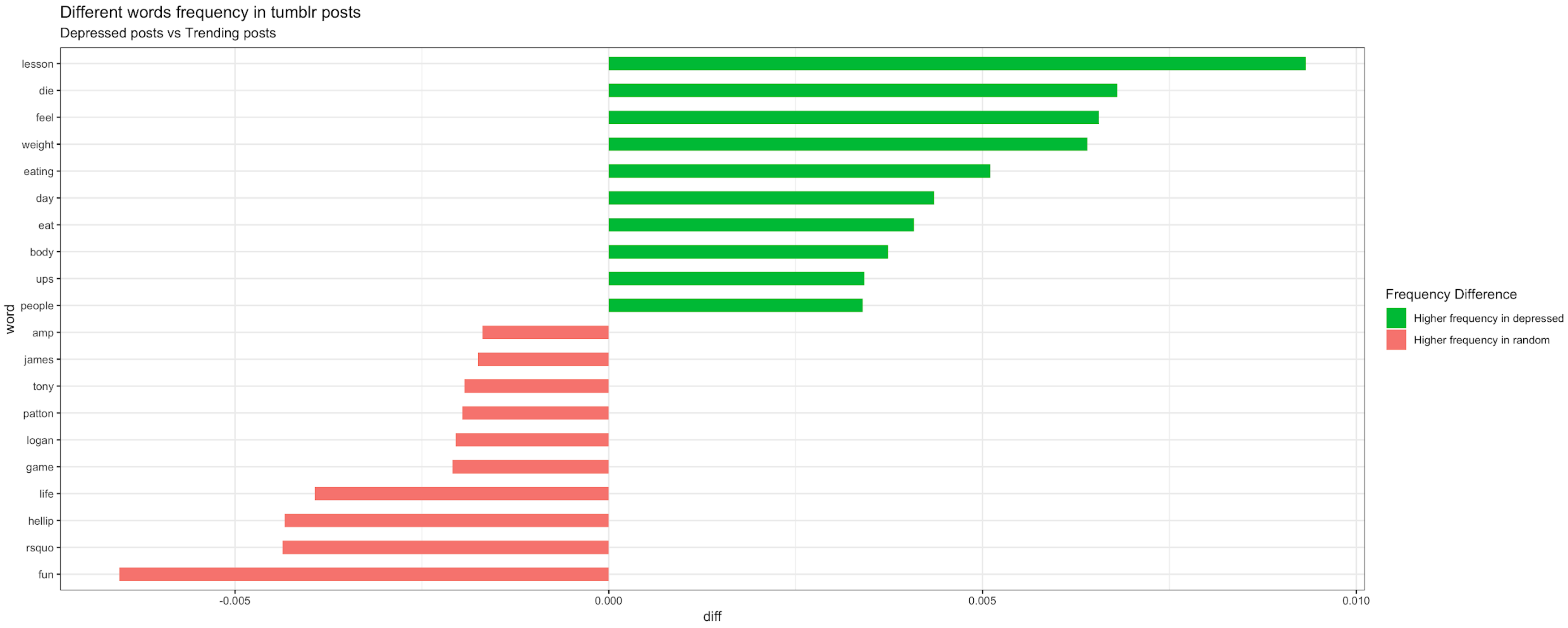
COMMENTS



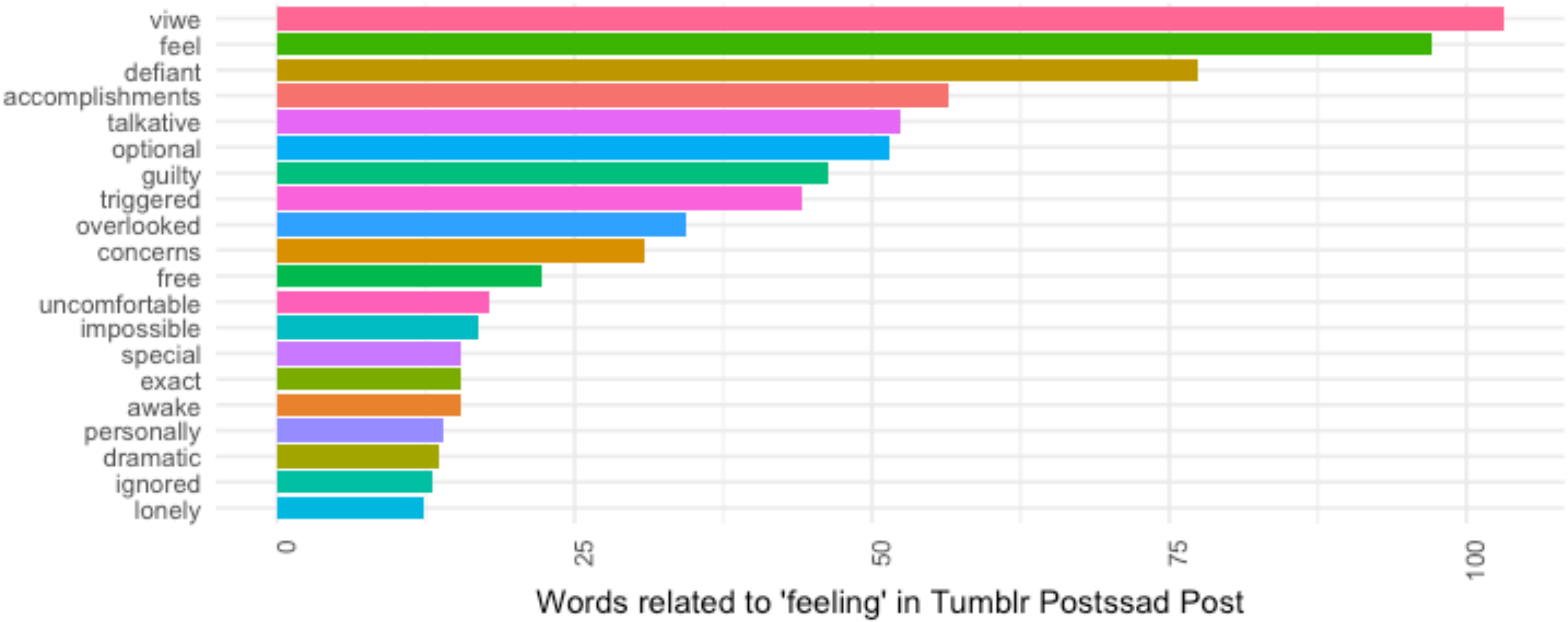
Reddit Summary

Broadly looking at unigrams, users talk about key life domains and receive support and empathy from commenters. Some users treat Reddit as a social media site (talking about daily frustrations, feelings, etc.), while others treat it as a support forum (looking for advice and guidance).

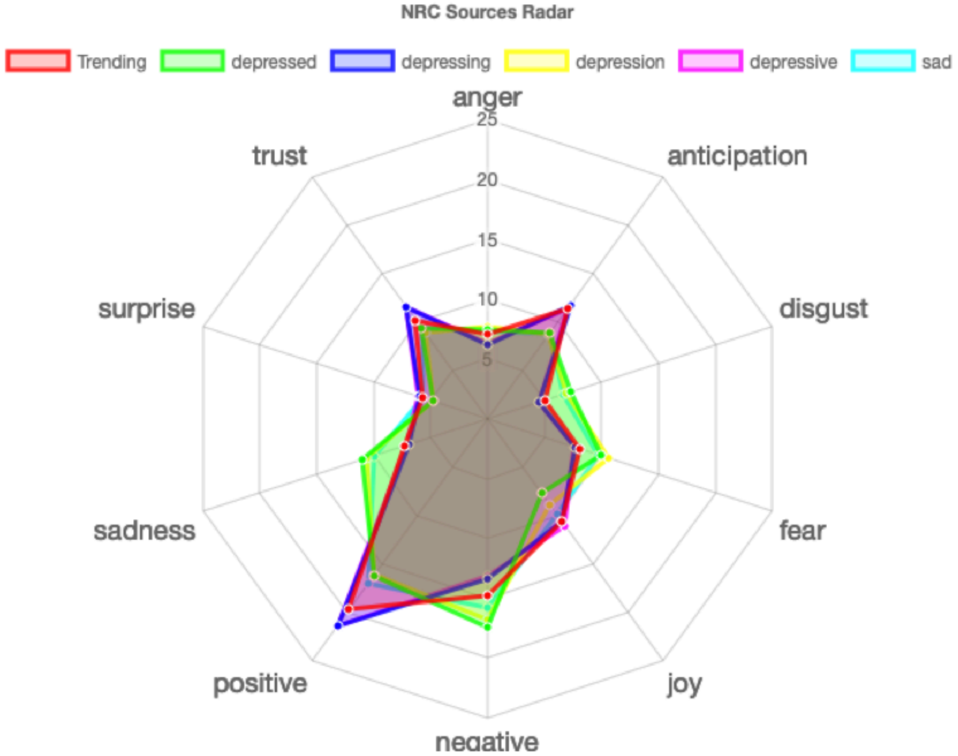
Tumblr - DICTIONARY ANALYSIS

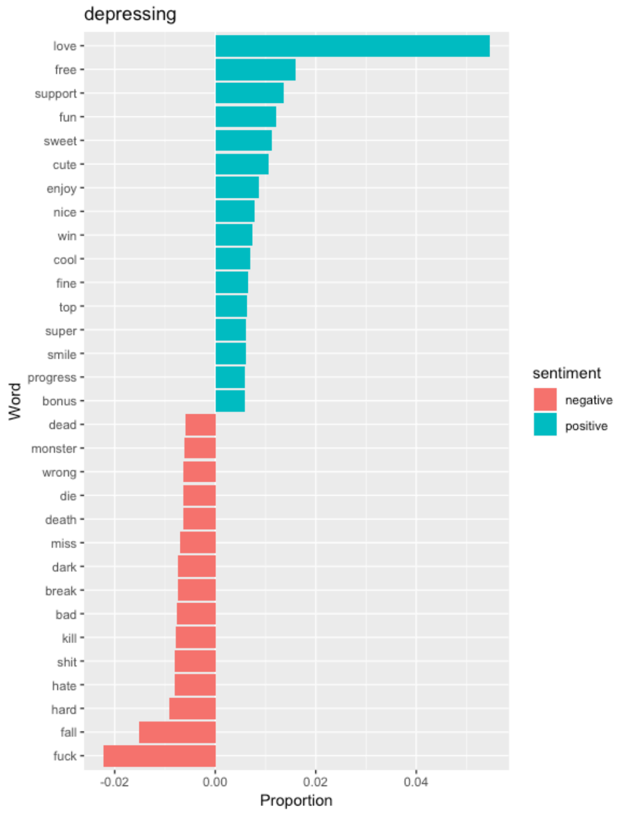


Tumblr - Dive into ‘Feel’ - TEXT NETWORK



Tumblr - SENTIMENT ANALYSIS





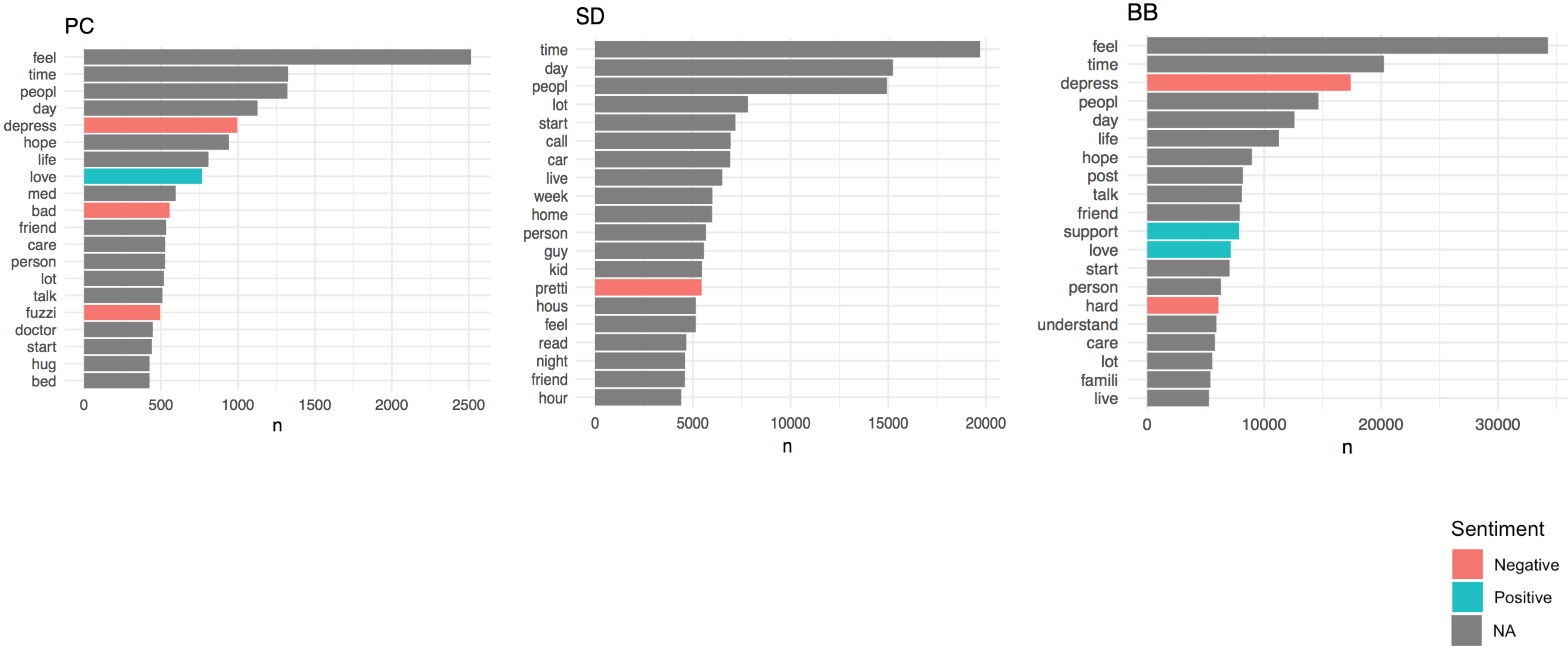
Tumblr Summary

Express personal feelings like ‘guilty’, ‘concerned’

‘#Depressing’ Posts tend to be more supportive

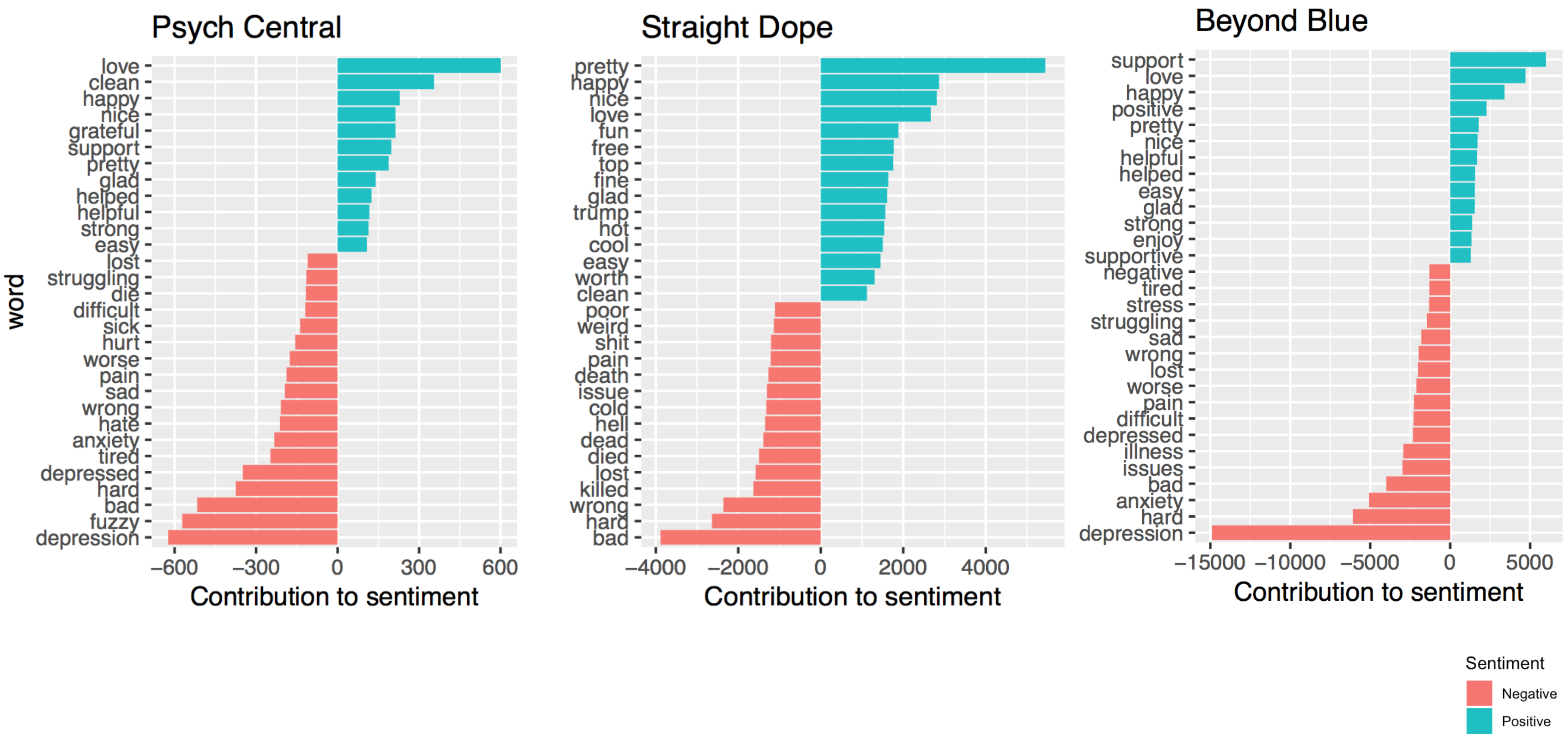
Forums - FREQUENT WORDS

Forum



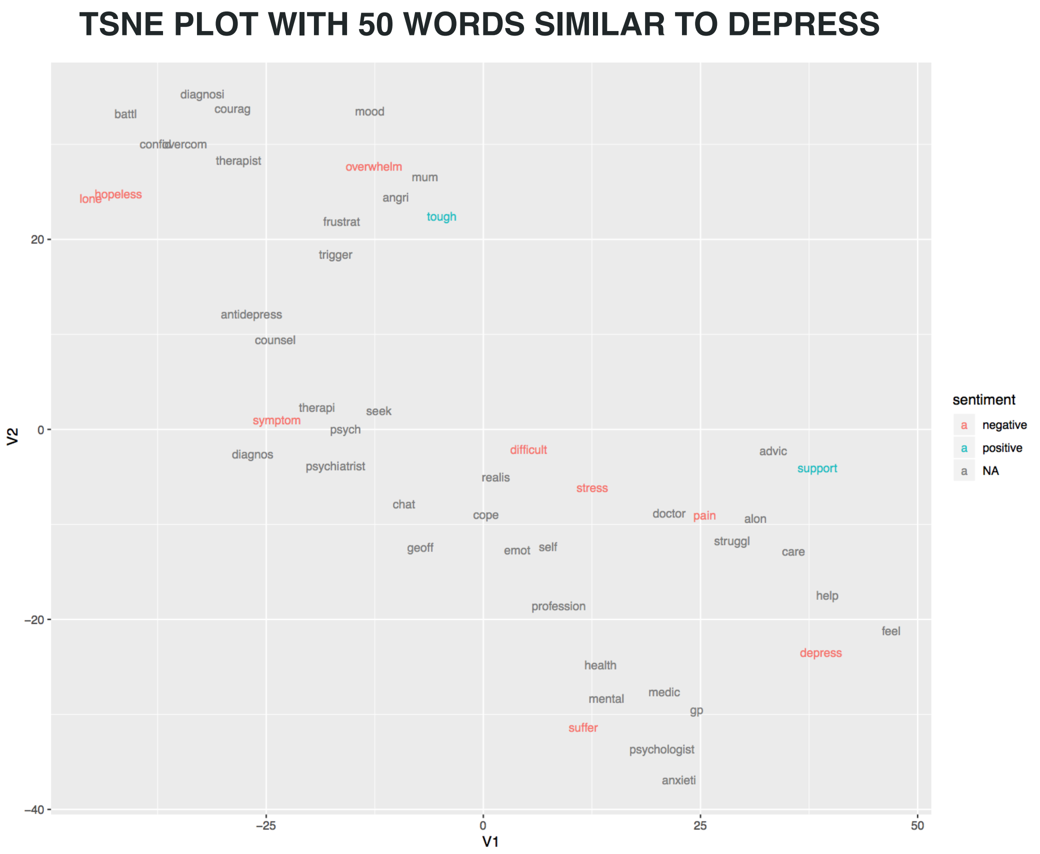
Forums - SENTIMENT ANALYSIS

Forum



Forums - EMBEDDINGS

Forum



Forums & Blogs - Text Network Analysis

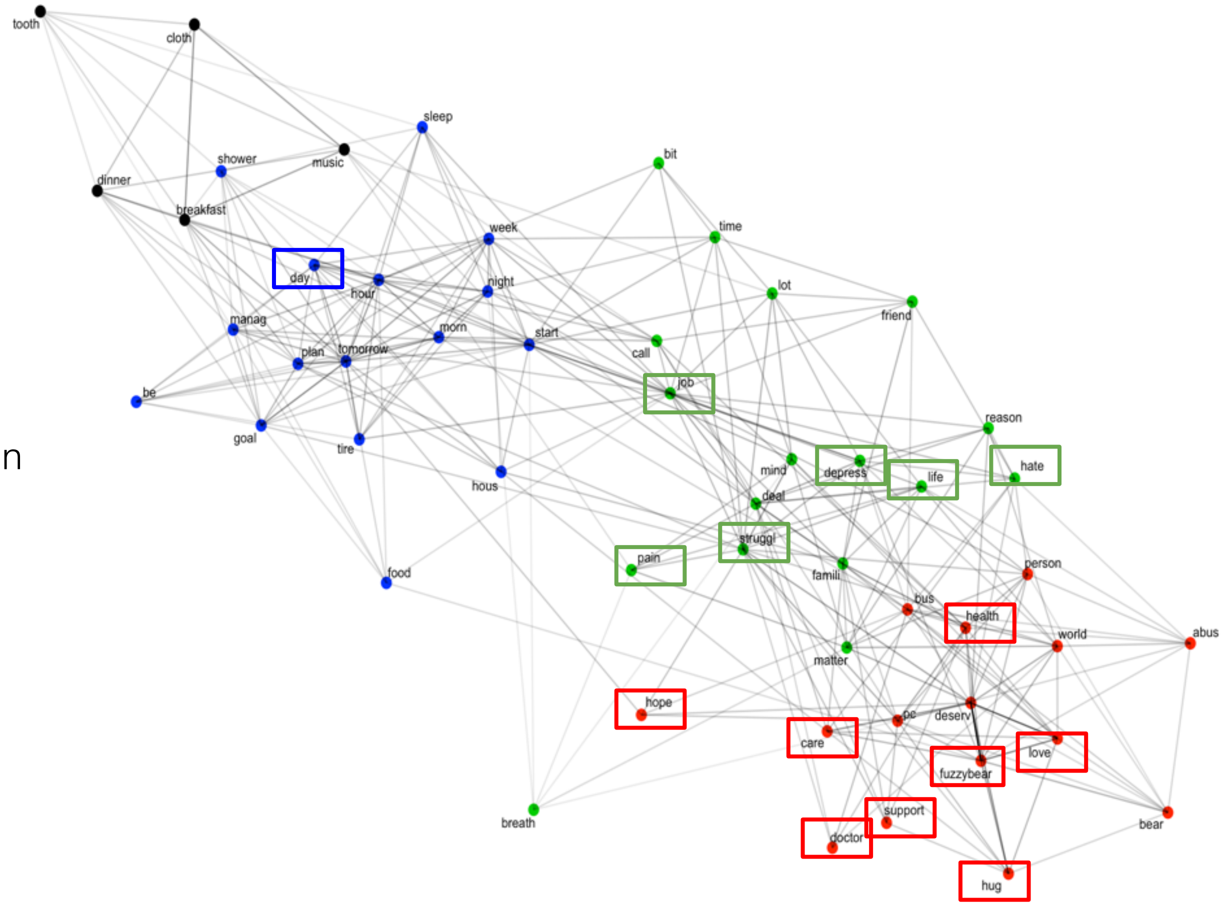
Forum

Psychcentral (PC)

Nodes represent words

Edges represent the use of two nodes(words) by the same person

Drop nodes and edges with low frequencies



Forums & Blogs - Text Network Analysis

Forum

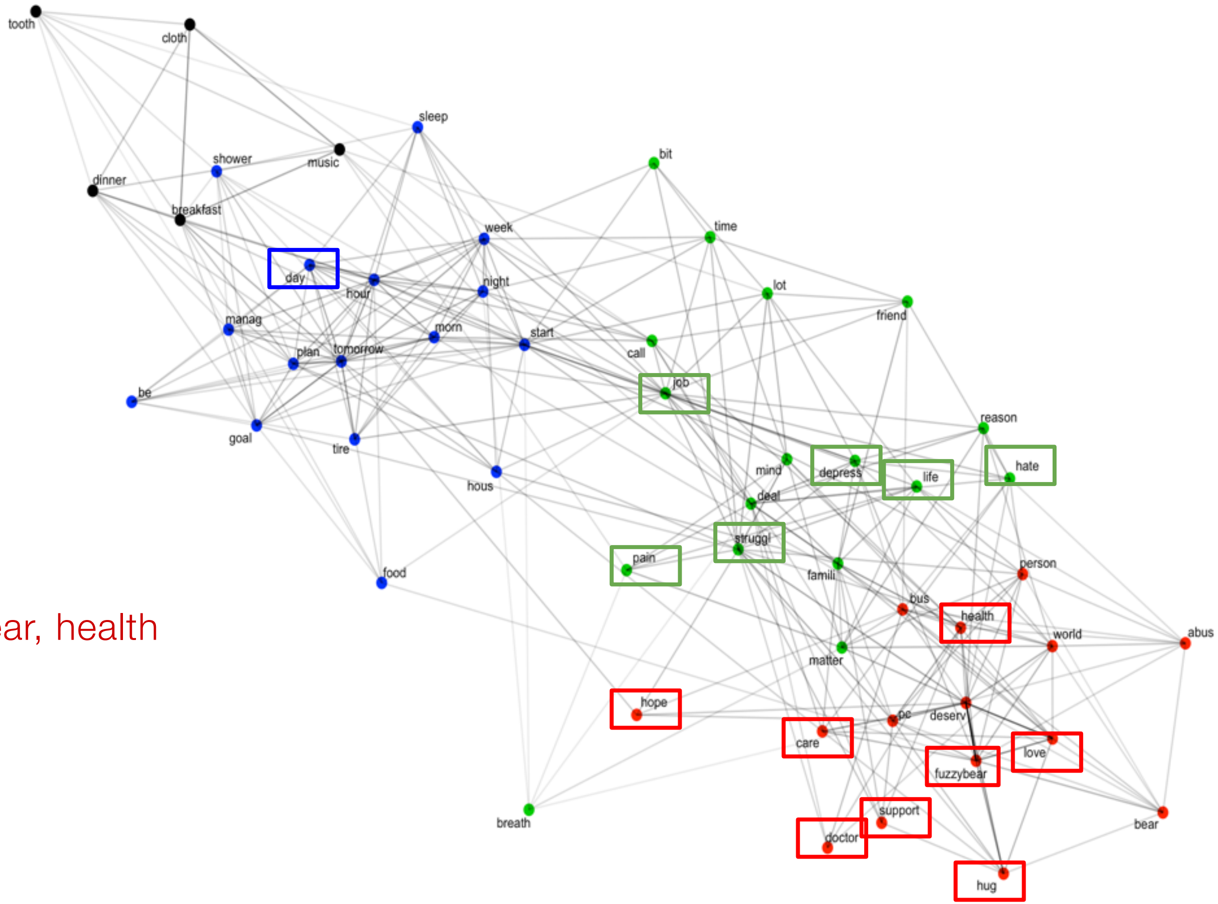
Psychcentral (PC)

Blue & Black: daily words

Green: depressive words

Red: supportive words

Central: stuggl, depress, fuzzybear, health

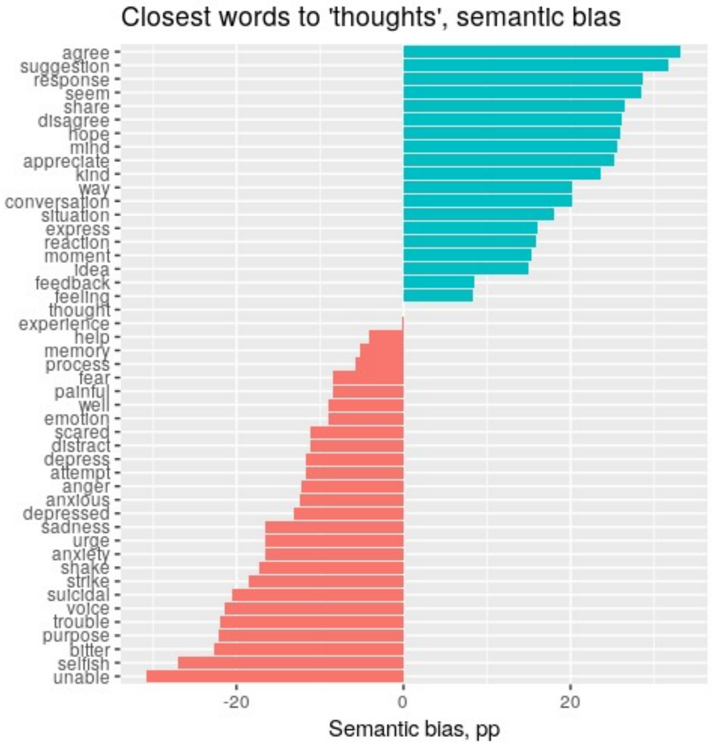


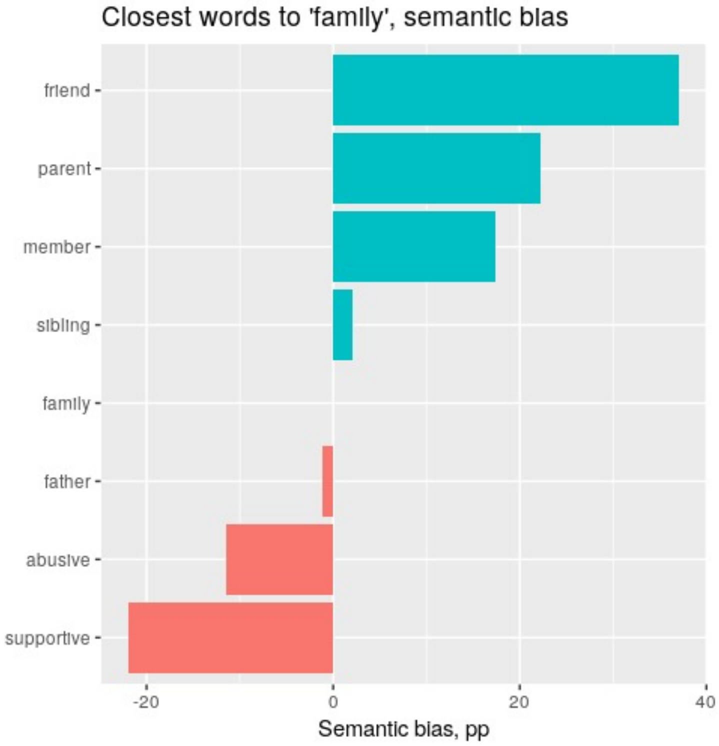
Forums Summary

People seek support and help in forums, they are open to share more personal things like the process of therapy and daily lives.

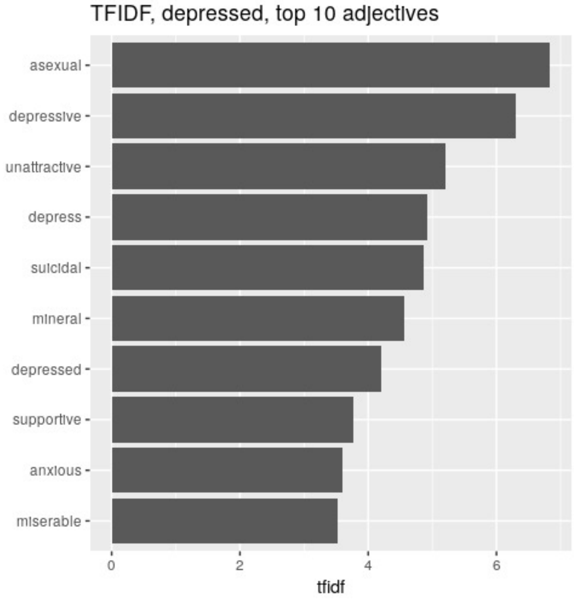
We found that absolutist words were more frequent in depressed forums compared to the random sample.

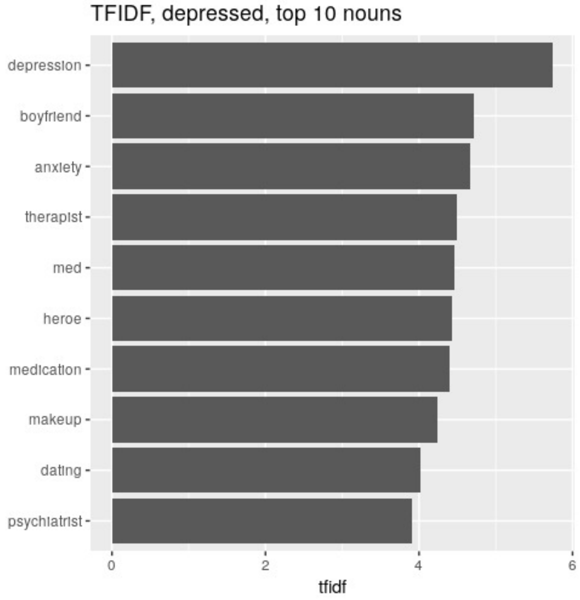
Early Risk Detection - WORD2VEC SEMANTIC BIAS: THOUGHTS, FAMILY

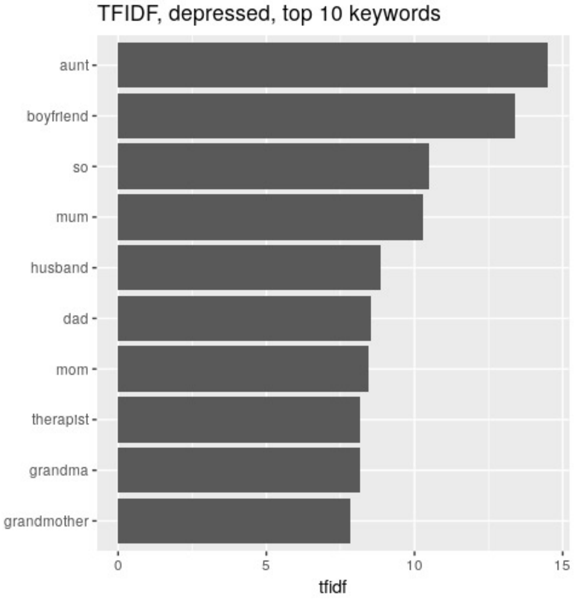




Early Risk Detection - TFIDF: TOP WORDS IN DEPRESSED PEOPLE

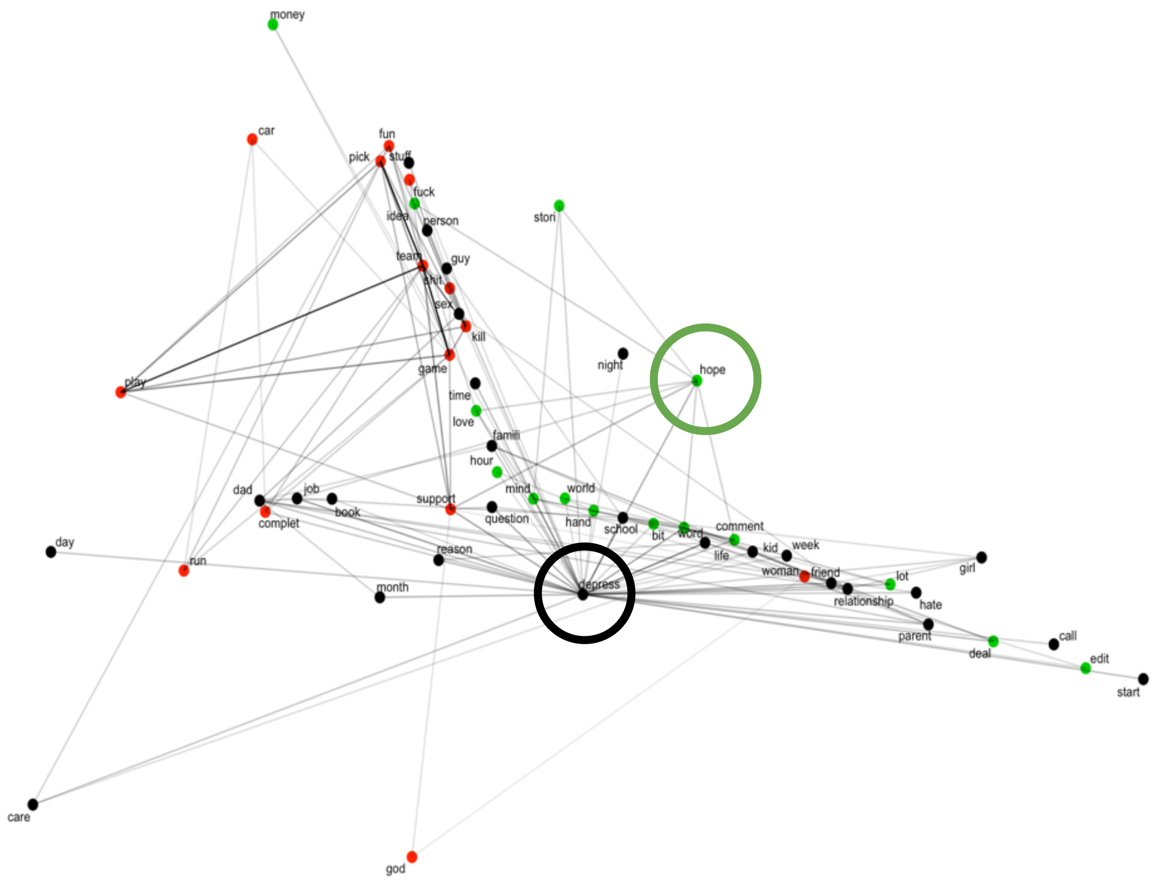






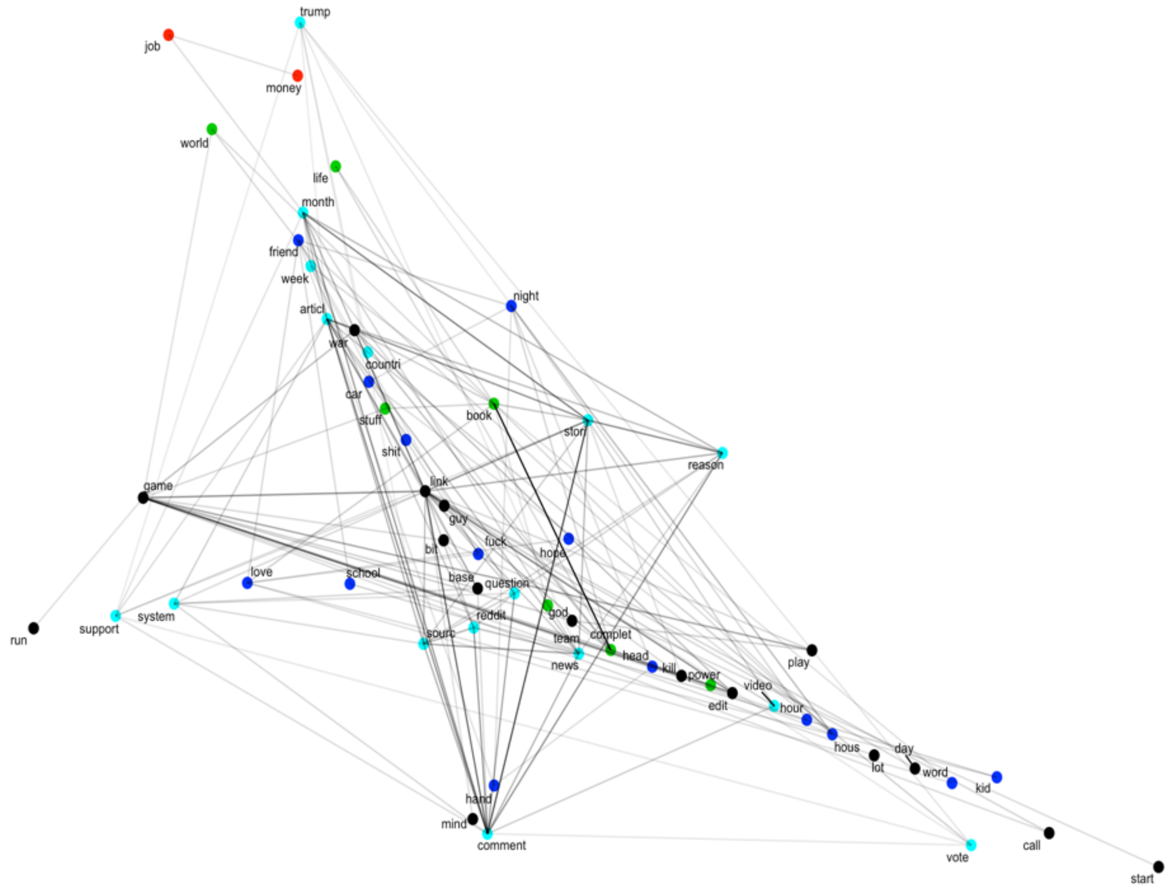
Early Risk Detection - Text Network Analysis

ER Depressed



Early Risk Detection - Text Network Analysis

ER General



Early Risk Detection Summary

Using word2vec we were able to detect a semantic bias between depressed people and not depressed people.

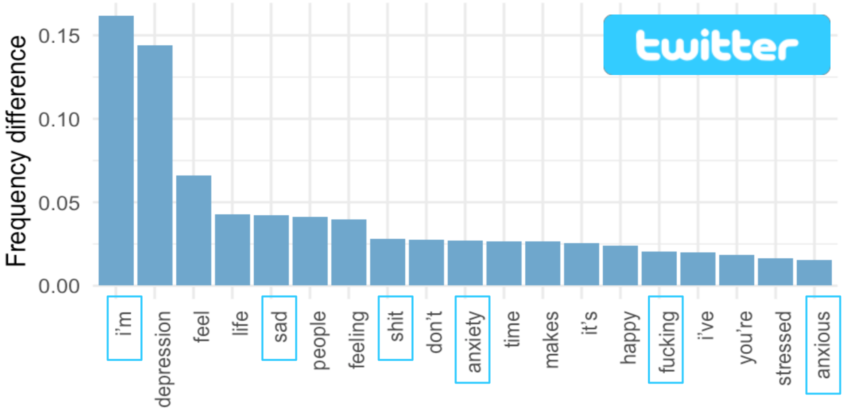
Part 3

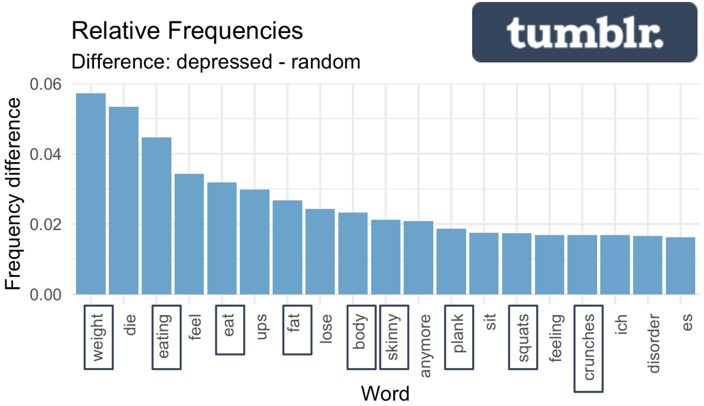
Social Media Platform Comparisons

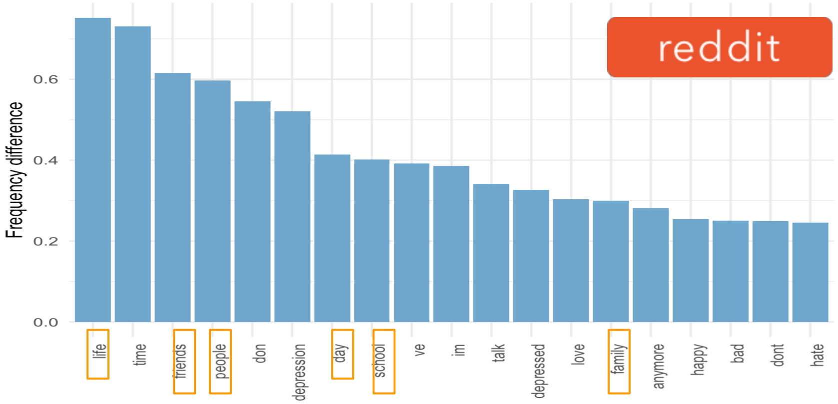
Dictionary-Based Analysis: Relative Frequencies

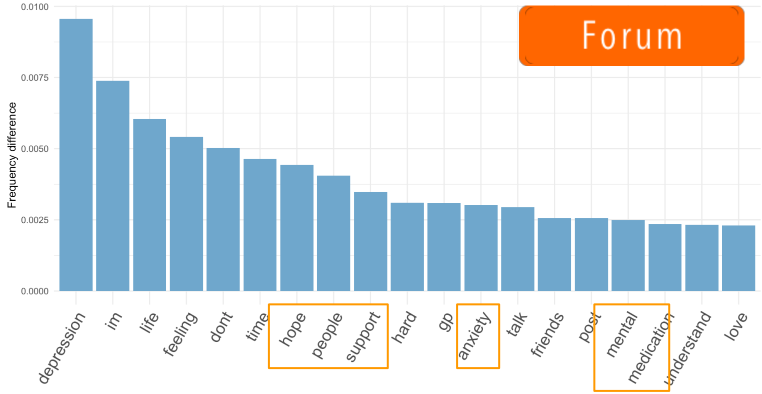
WORDS MORE LIKELY TO BE IN 'DEPRESSED' SAMPLE

DIFFERENCE: DEPRESSED - RANDOM

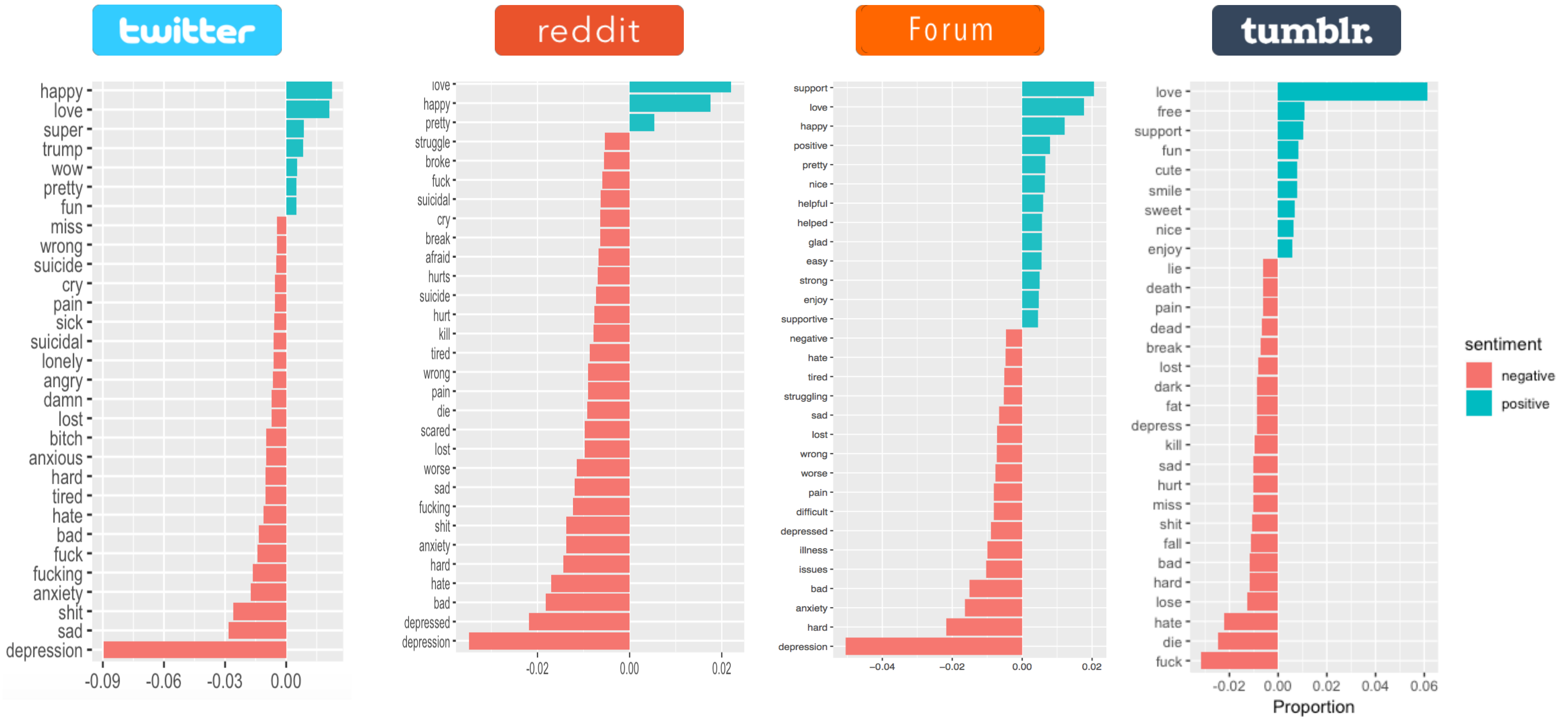








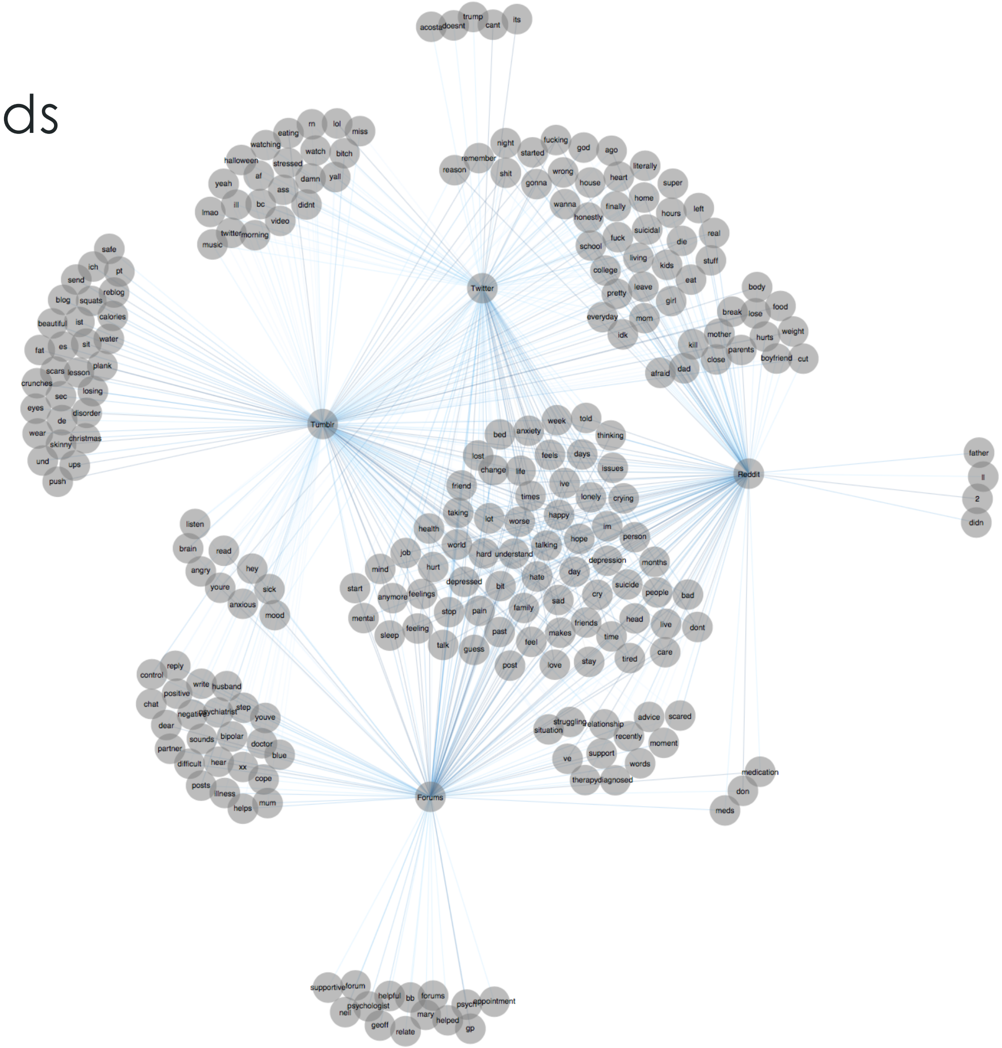
Sentiment Analysis: Bing Dictionary - 30 TOP WORDS



DEMO

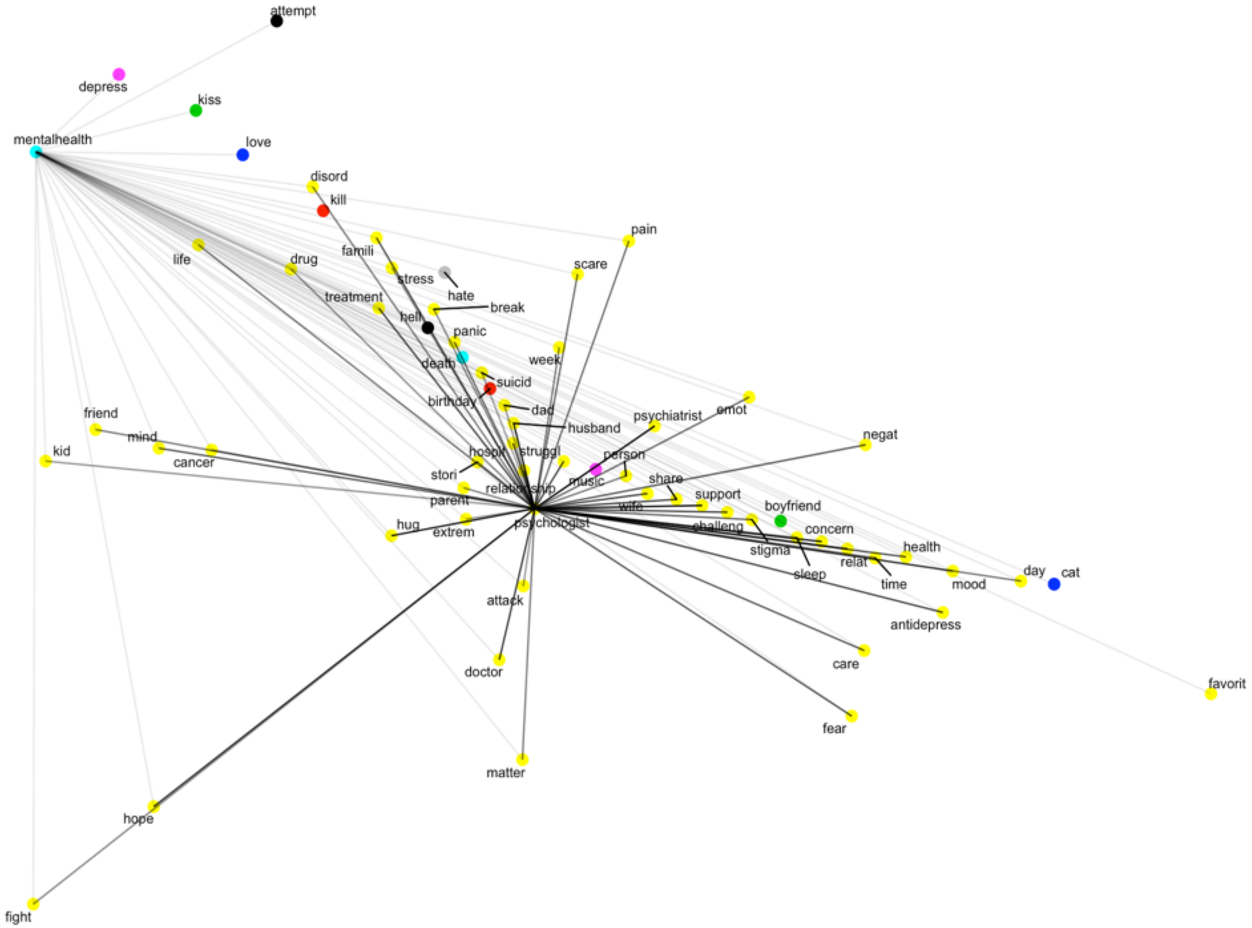
NCR Combined Source

Venn Diagram Network: Words



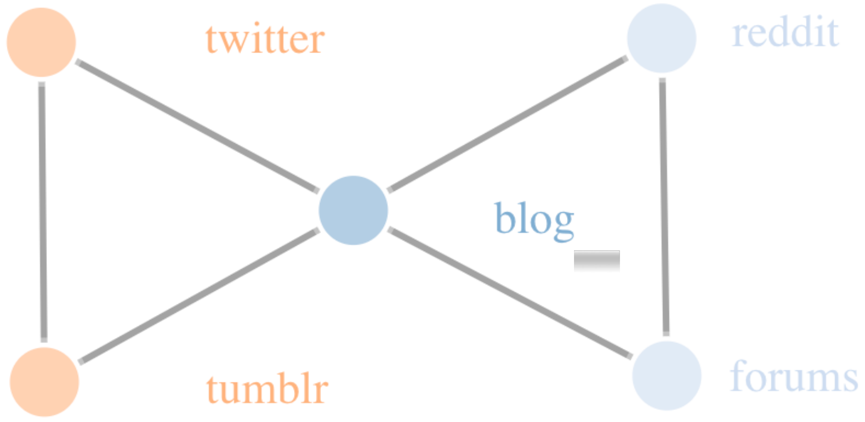
Combined Network - WORDS

Top 100 words from each sources



Combined Network - PLATFORMS

Separation between social media platforms and blogs/forums



Part 4

Conclusions & Next Steps

Conclusions

- Depression is not expressed uniformly across social media platforms and blogs
- Text across a variety of social media platform and forums reflect the findings of previous research examining language of those suffering from depression

  > High use of first person singular pronouns, increased negative sentiment, swearing, anxiety, dealth, everyday life

- Language around depression on Reddit more closely resembles forums, while text on social media sites Tumblr and Twitter are similar to each other.
- Public health organizations can use this delineation to better target care campaigns (ex. Focus eating disorder outreach on Tumblr)

Challenges

- Issues related to scraping depression-related data
  - Lack of ground truth
  - Differences in blog and forum formatting
  - Anonymity vs. Identification
  - Subjectivity to time period of data collection
  - Special Characters
- Difficulty interpreting topic models and text networks
  - Depressive sentiment is often found in hidden subtext
  - More time and data might yield different results
- Dealing with broadness of ‘depression’
  - Mental health disorders are overlapping in symptom nature (ex. Anxiety, suicidal ideation, etc.)
  - Users themselves often do not know how to express what they are going through

Next Steps

- Additional analysis
    - LIWC
    - Part-of-speech tagging
- Further comparison between our findings and previous research
- Follow-up study to find a solid ground truth
    - Psychological assessment
    - Social media handles
- Improve upon networking and topic modeling approaches to gather new insights on depressed population.
- Build a classification algorithm to identify text from people potentially suffering from depression.

Thank You

Anna Berman, Viggy Kumaresan, Azucena Morales, Allen Wang, Sicong Zhao

Presented by LEAST SQUARES

References

Glen Coppersmith, Mark Dredze, and Craig Harman. 2014. Quantifying mental health signals in Twitter. In Proceedings of the Workshop on Computational Linguistics and Clinical Psychology: From Linguistic Signal to Clinical Reality, pages 51–60.

Glen Coppersmith, Mark Dredze, Craig Harman, and Kristy Hollingshead. 2015. From ADHD to SAD: Analyzing the language of mental health on Twitter through self-reported diagnoses. In Proceedings of the 2nd Workshop on Computational Linguistics and Clinical Psychology: From Linguistic Signal to Clinical Reality, pages 1–10.

Philip Resnik, William Armstrong, Leonardo Claudino, and Thang Nguyen. 2015a. The University of Maryland CLPsych 2015 shared task system. In Proceedings of the 2nd Workshop on Computational Linguistics and Clinical Psychology: From Linguistic Signal to Clinical Reality, pages 54–60.

Mohanned Al-Mosaiwi and Tom Johnstone. 'In an Absolute State: Elevated Use of Absolutist Words Is a Marker Specific to Anxiety, Depression, and Suicidal Ideation'. *Clinical Psychological Science,* Vol. 6(4), 2018 pp. 529–542.

Munmun De Choudhury, Michael Gamon, Scott Counts, and Eric Horvitz. 2013. Predicting depression via social media. ICWSM, 13:1–10.

References cont.

Stephanie Rude et al. “Language Use of Depressed and Depression-Vulnerable College Students.” *Cognition & Emotion*, vol. 18, no. 8, 2004, pp. 1121–1133.

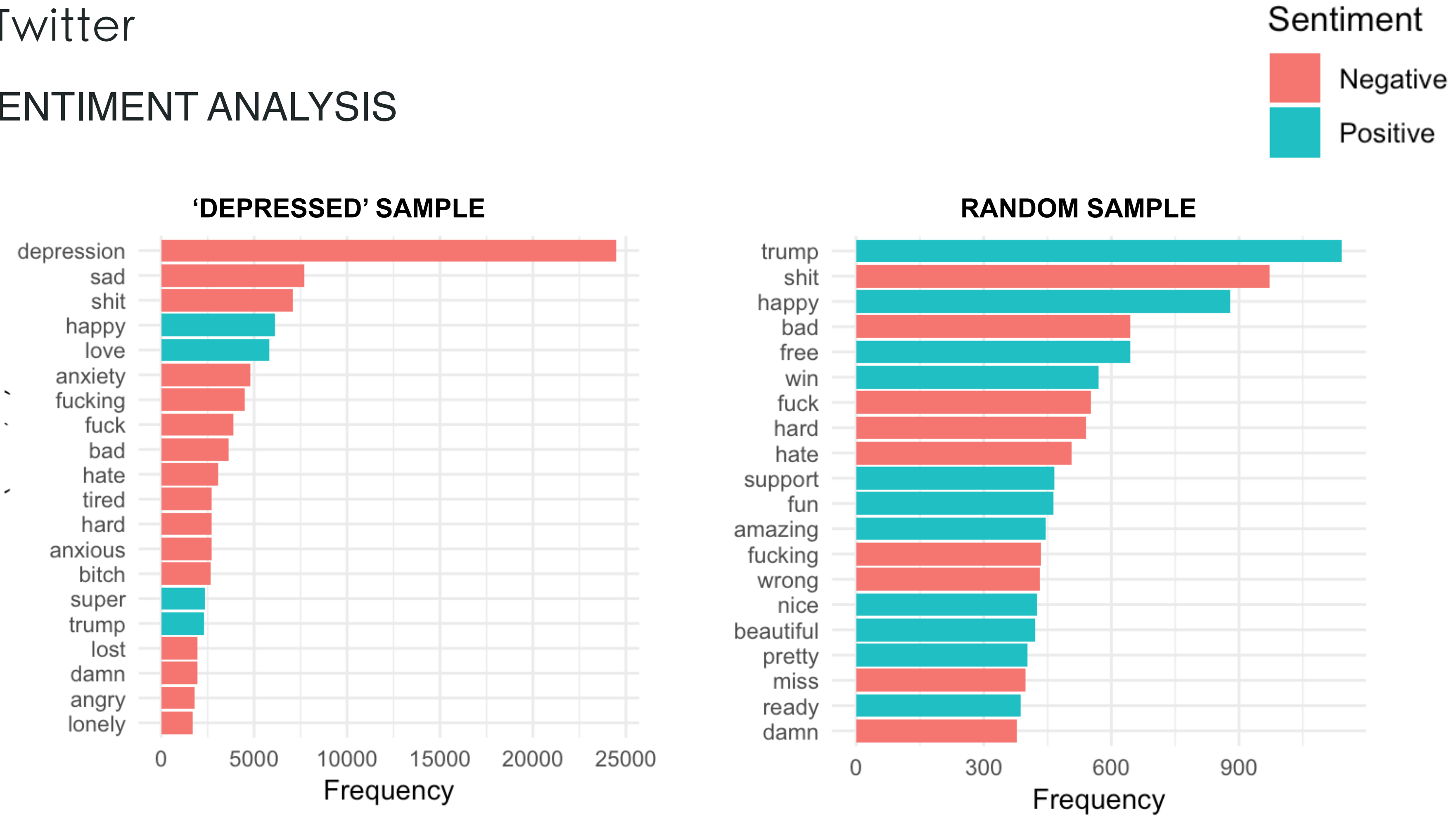
Yla R. Tausczik and James W. Pennebaker. “The Psychological Meaning of Words: LIWC and Computerized Text Analysis Methods.” *Journal of Language and Social Psychology*, vol. 29, no. 1, 2009, pp. 24–54.

Appendix

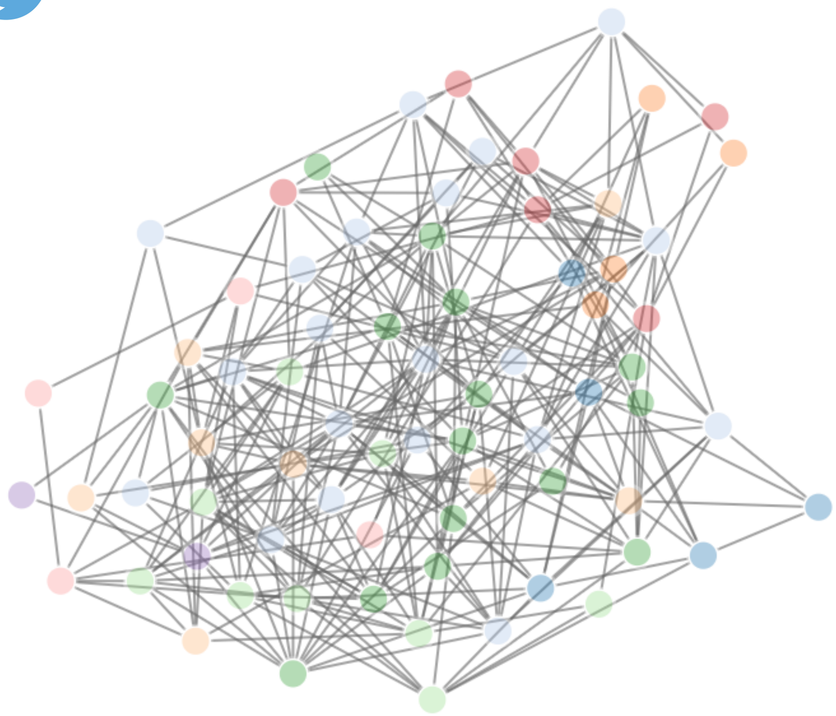
Individual Sources

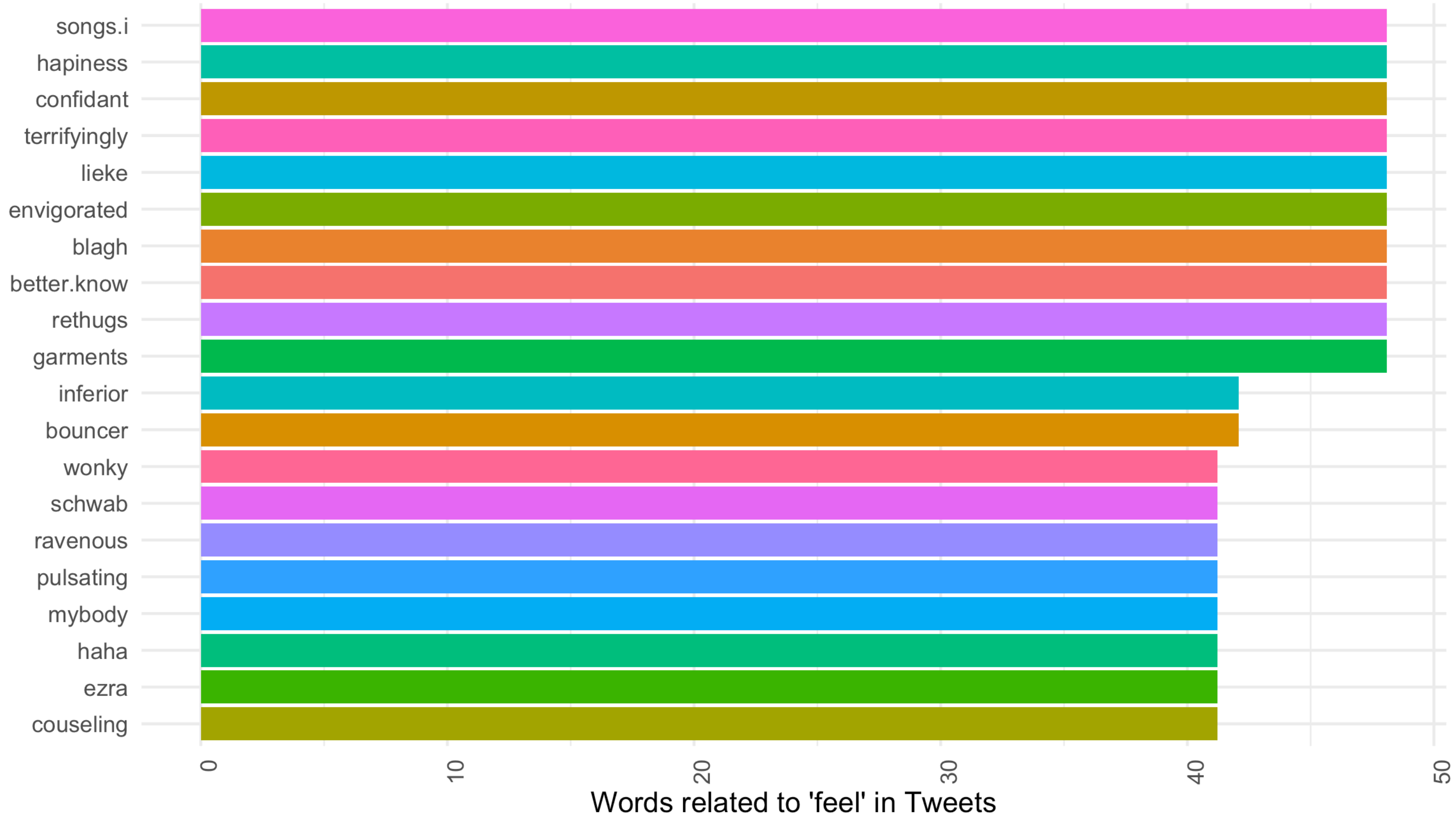
Twitter

SENTIMENT ANALYSIS



WITHIN PLATFORM COMPARISON

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pulsating
mybody
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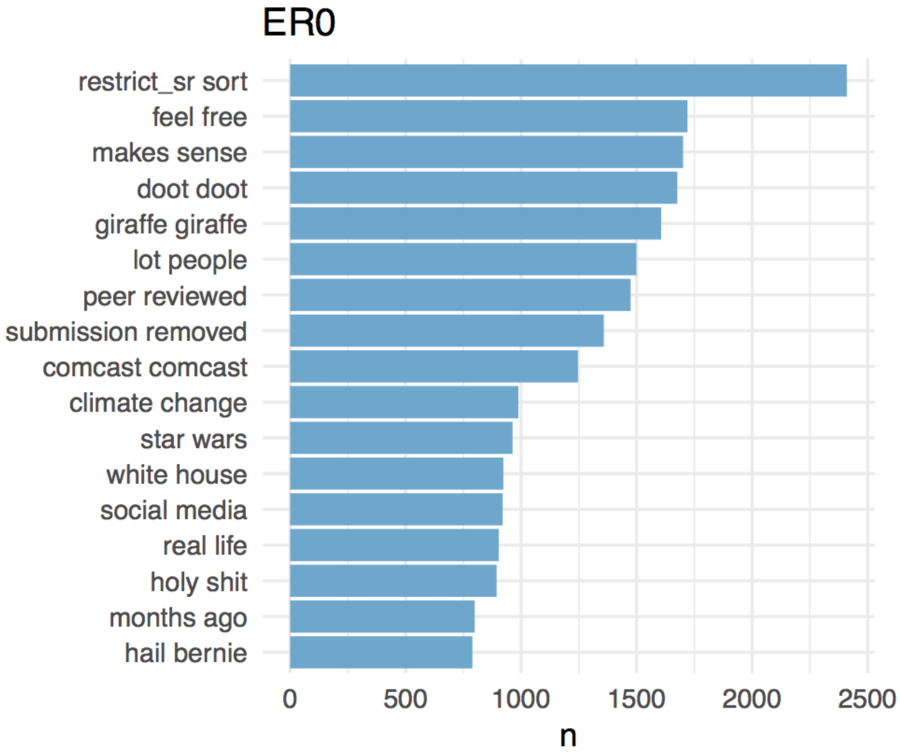
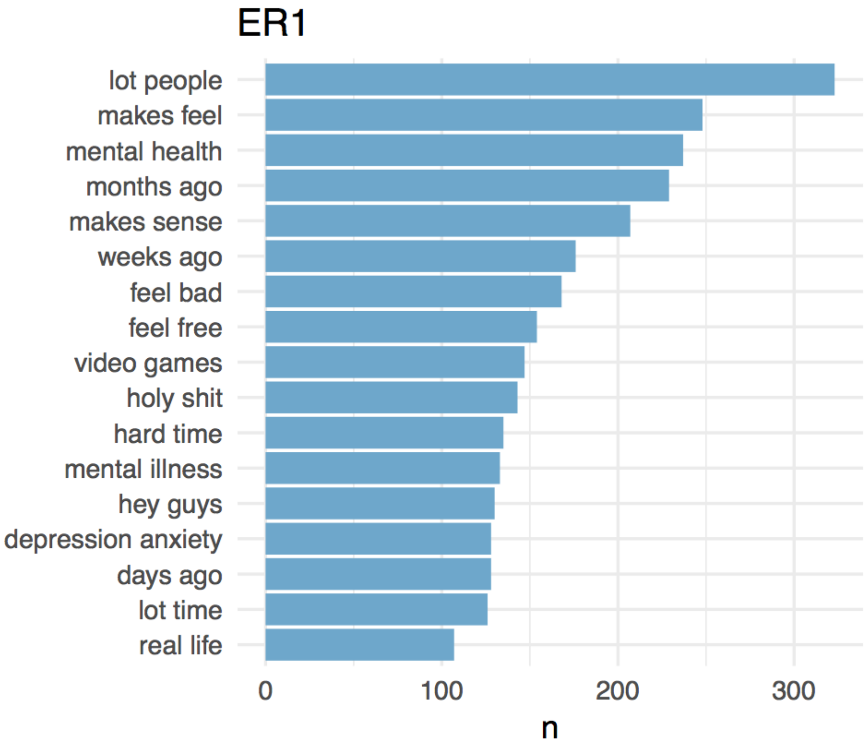
Words related to 'feel' in Tweets

Early Risk Detection

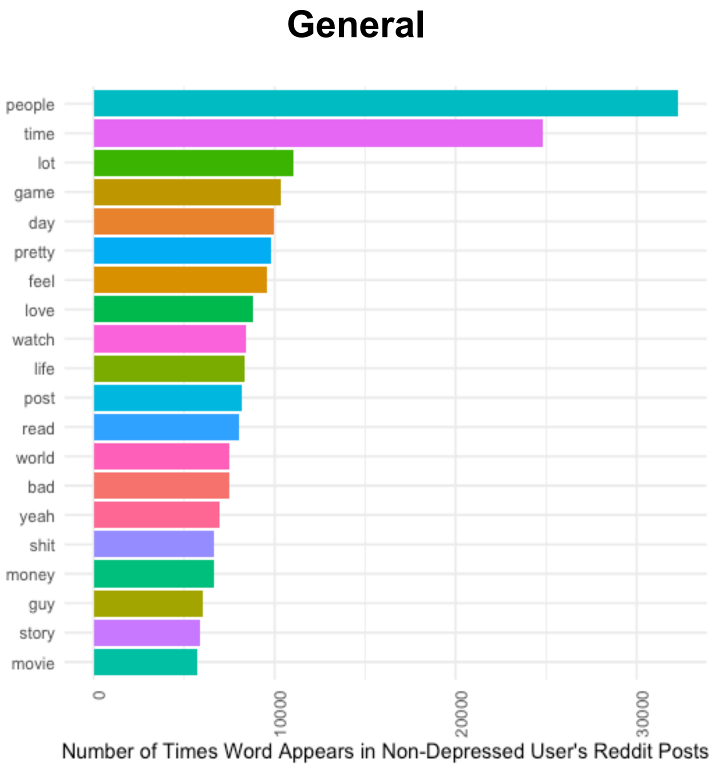
FREQUENT BIGRAMS

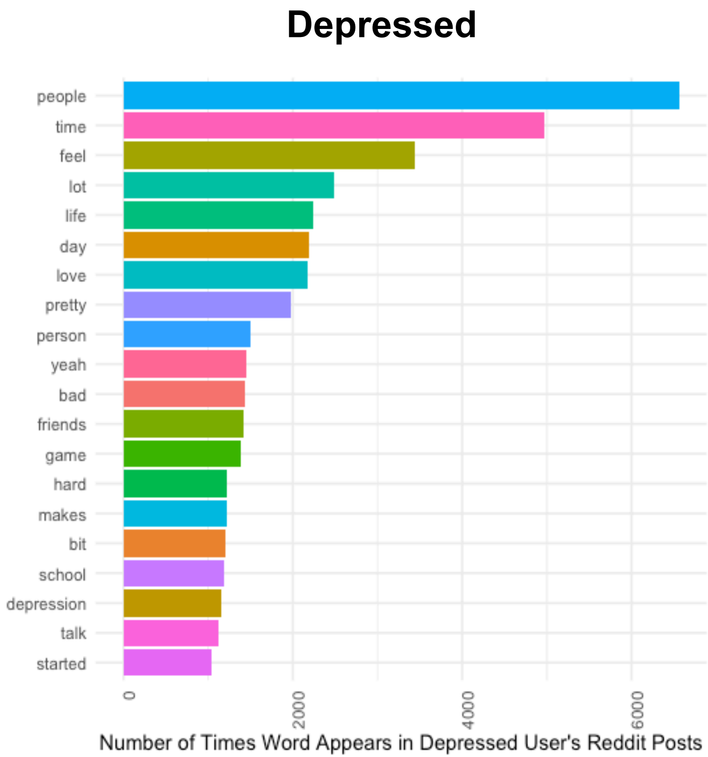




Early Risk Detection

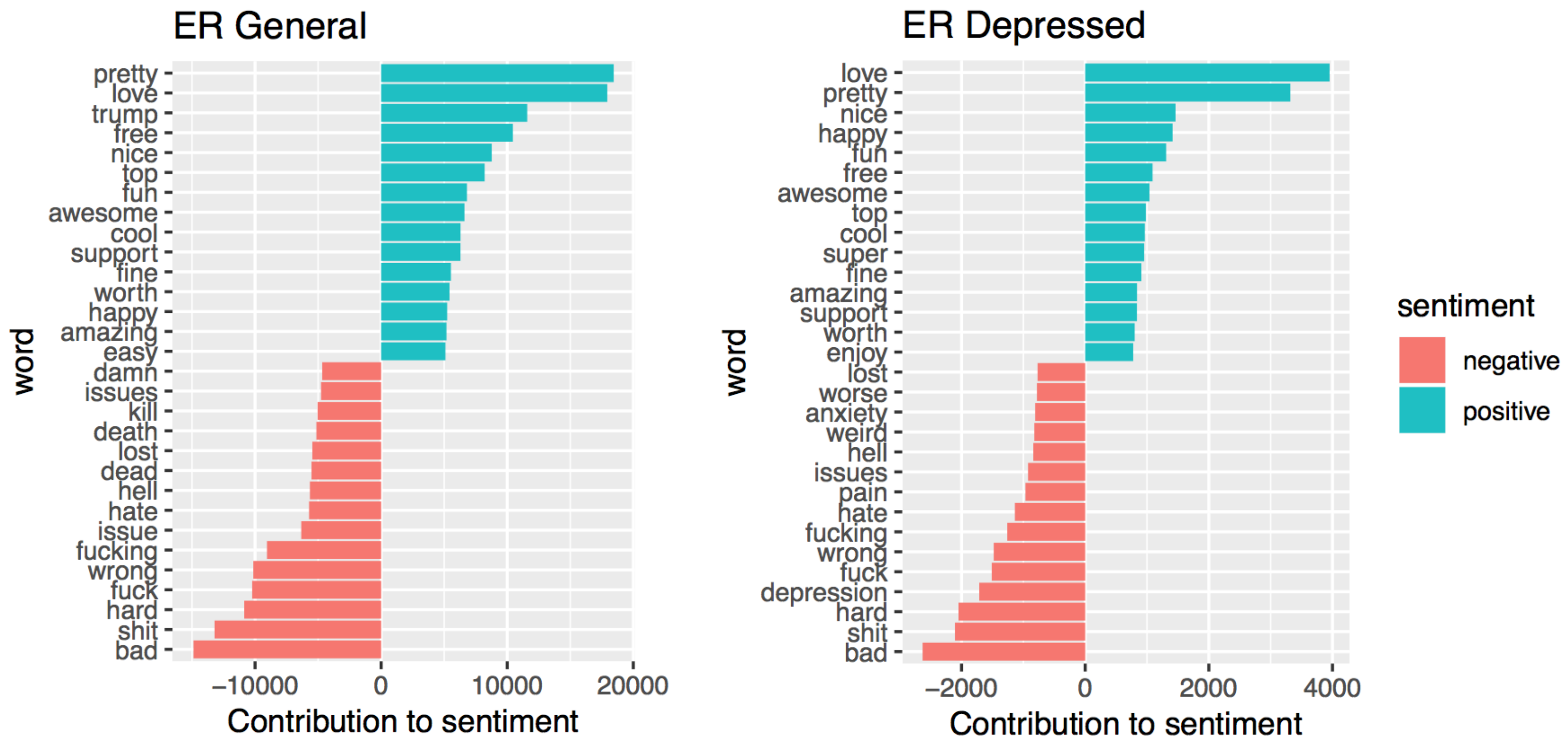
FREQUENT WORDS





Early Risk Detection

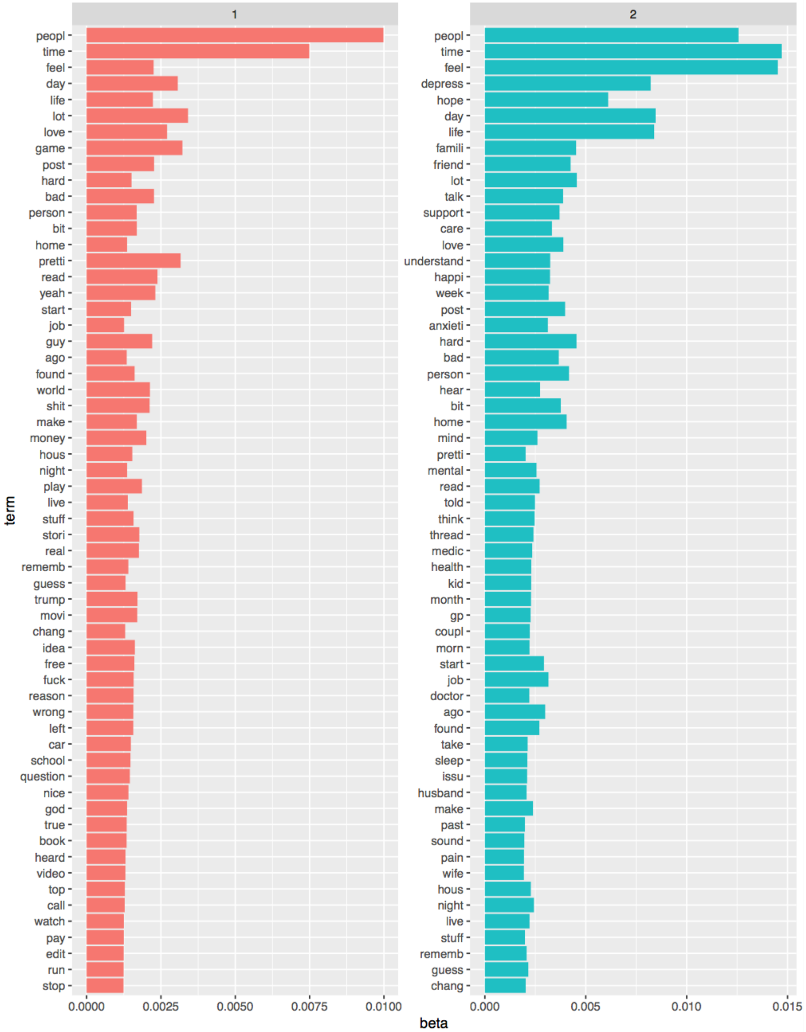
SENTIMENT ANALYSIS



ection

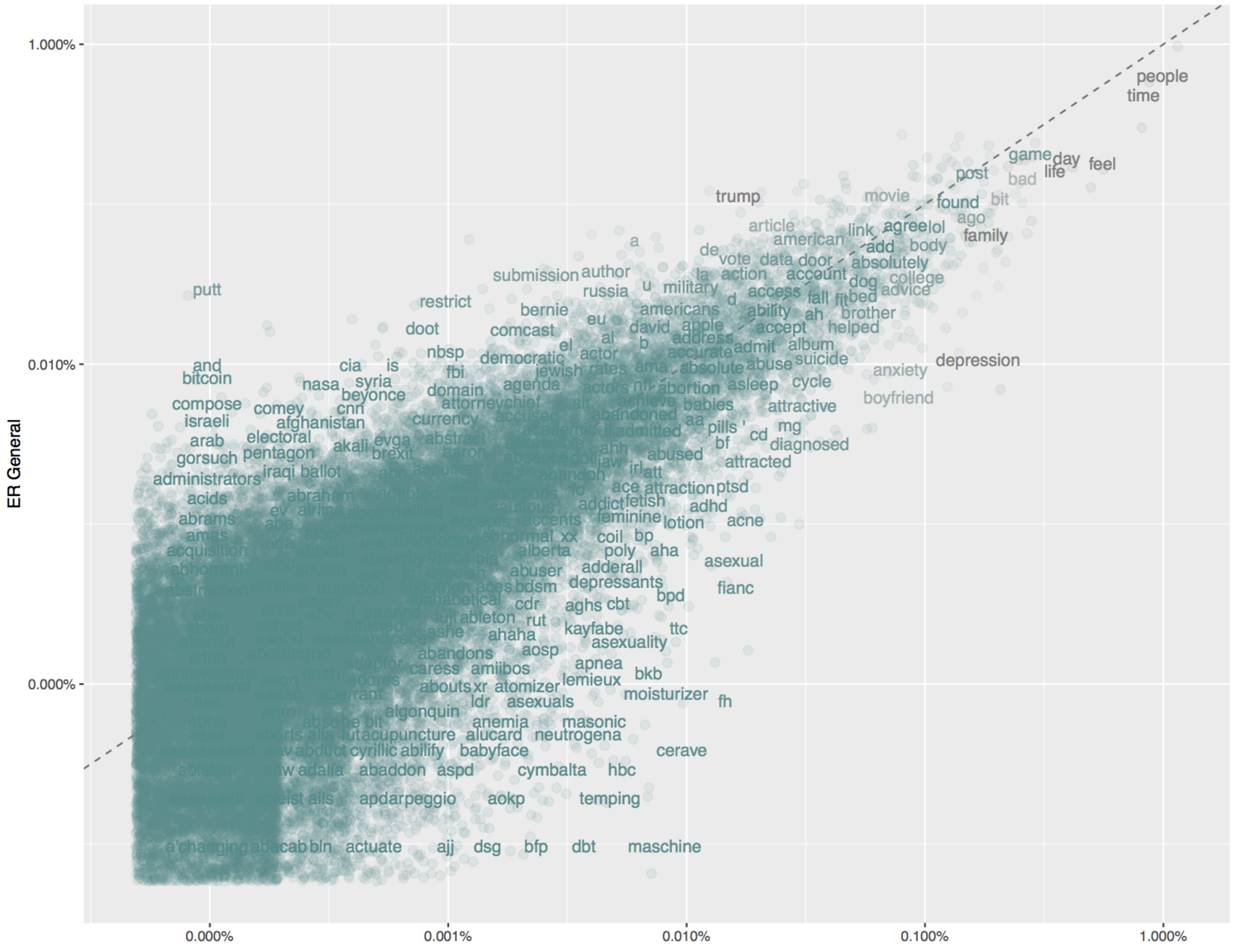
Is this a combination of all forum and ER data?

What's the takeaway?



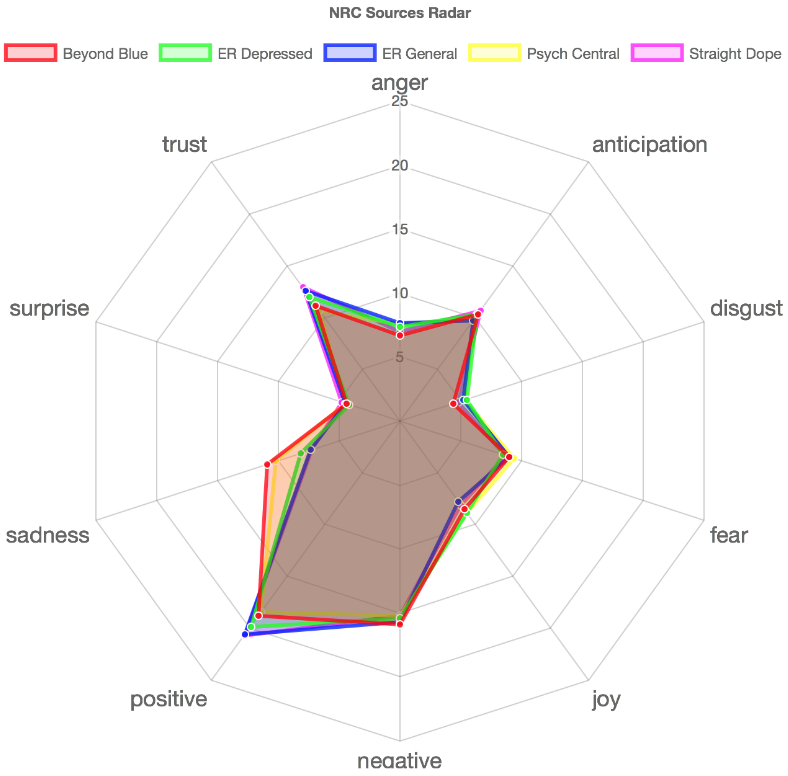
Early Risk Detection

SHARED WORDS



Forums & Early Risk Detection

NCR RADAR



negative
- Beyond Blue: 15.8676926983545
- ER Depressed: 15.4080296799323
- ER General: 15.6798440310295
- Psych Central: 15.2519276788088
- Straight Dope: 15.2317589417876

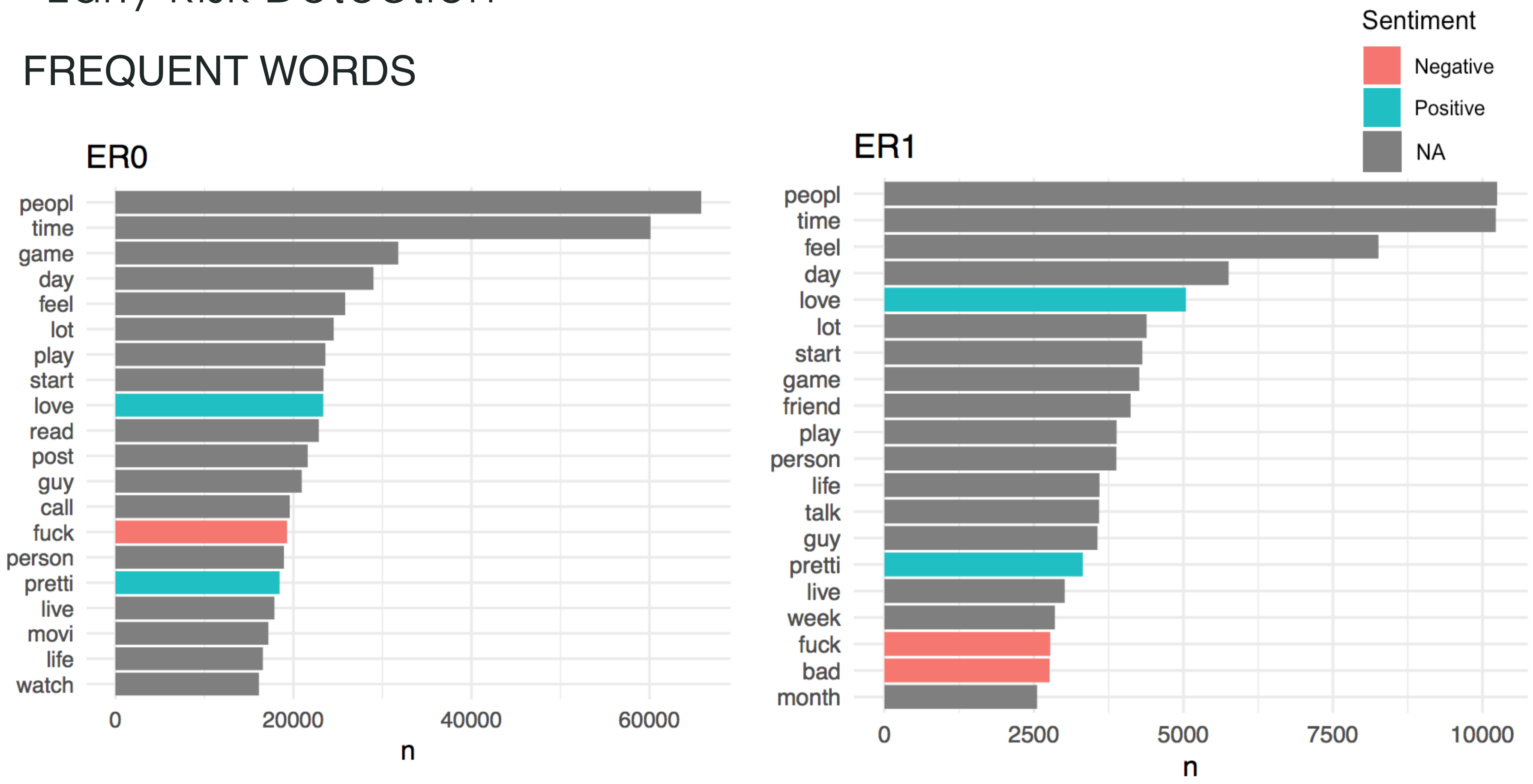
positive
- Beyond Blue: 18.8116628529371
- ER Depressed: 19.8573981641247
- ER General: 20.649817350242
- Psych Central: 18.3938225649207
- Straight Dope: 20.6663639192073

sadness
- Beyond Blue: 10.8990569252843
- ER Depressed: 8.10400312095713
- ER General: 7.28688597275556
- Psych Central: 10.1502260037224
- Straight Dope: 7.22524096707386

fear
- Beyond Blue: 8.98932823945067
- ER Depressed: 8.47022215231936
- ER General: 8.94323481852241
- Psych Central: 9.38137020296021
- Straight Dope: 8.66114388256332

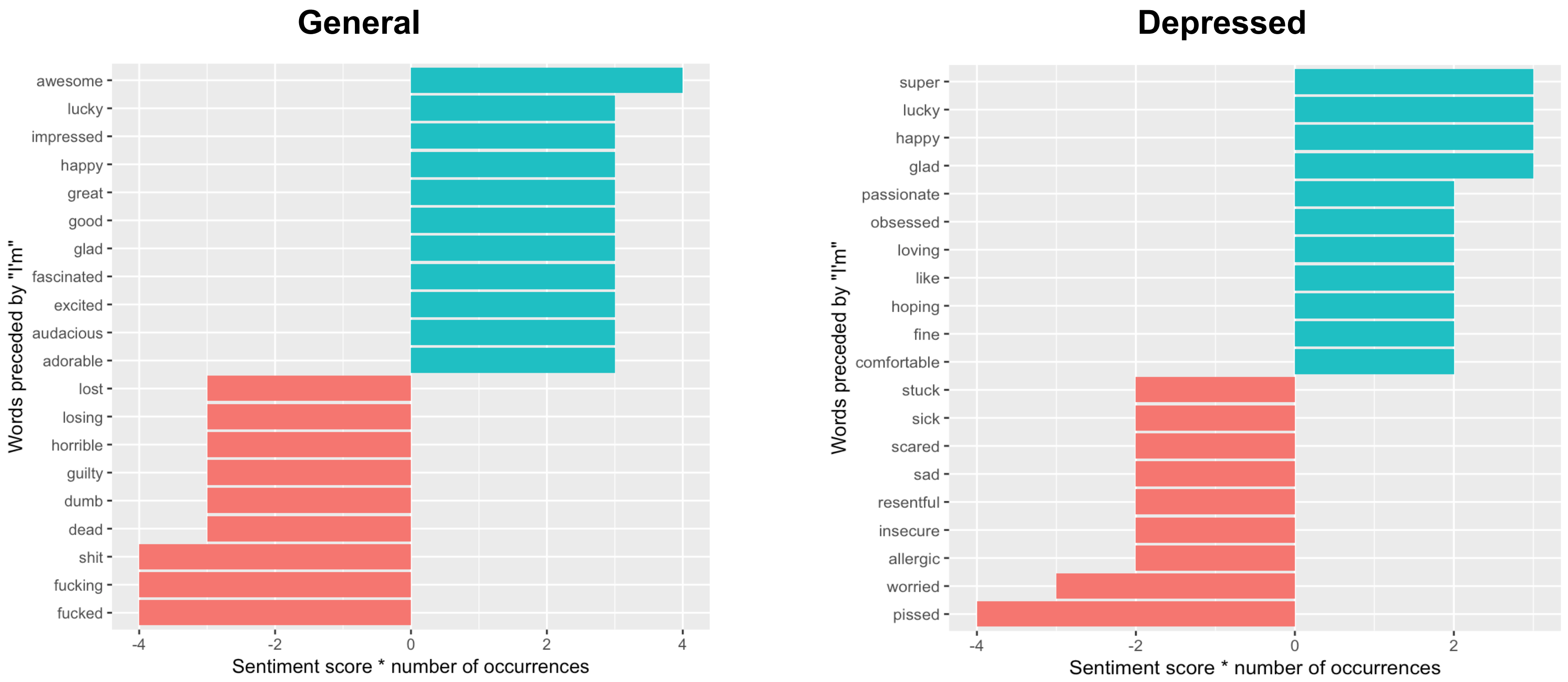
Early Risk Detection

FREQUENT WORDS



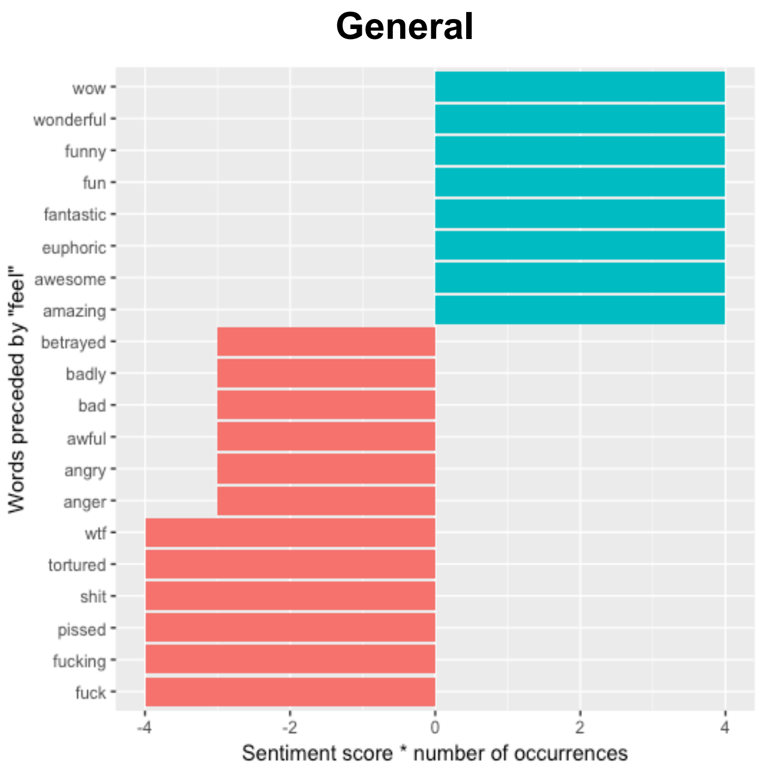
Early Risk Detection

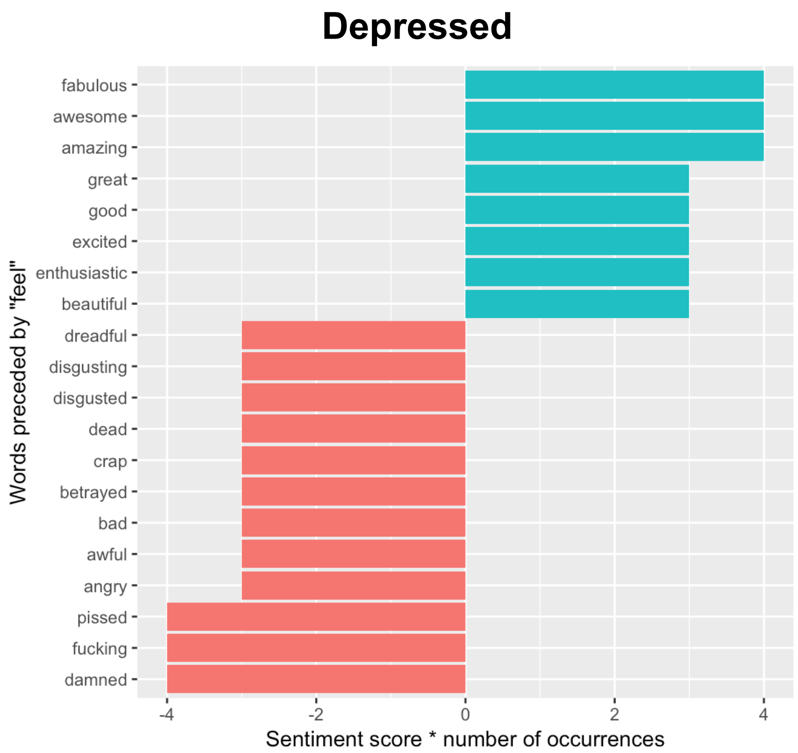
BIGRAMS SENTIMENT: ‘I’M __’



Early Risk Detection

BIGRAMS SENTIMENT: 'FEEL __'

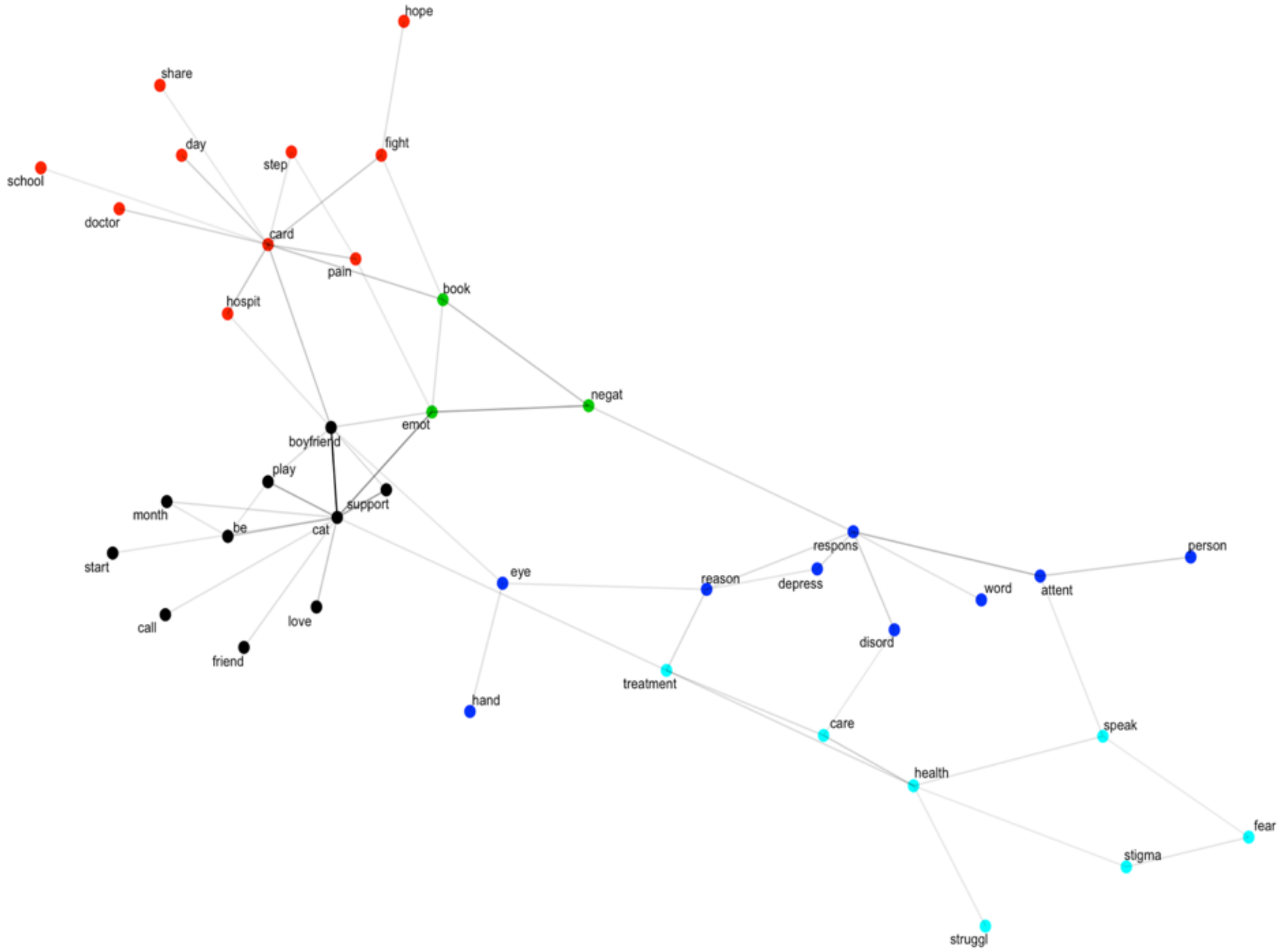




Forums
and Blogs

Text Network Analysis

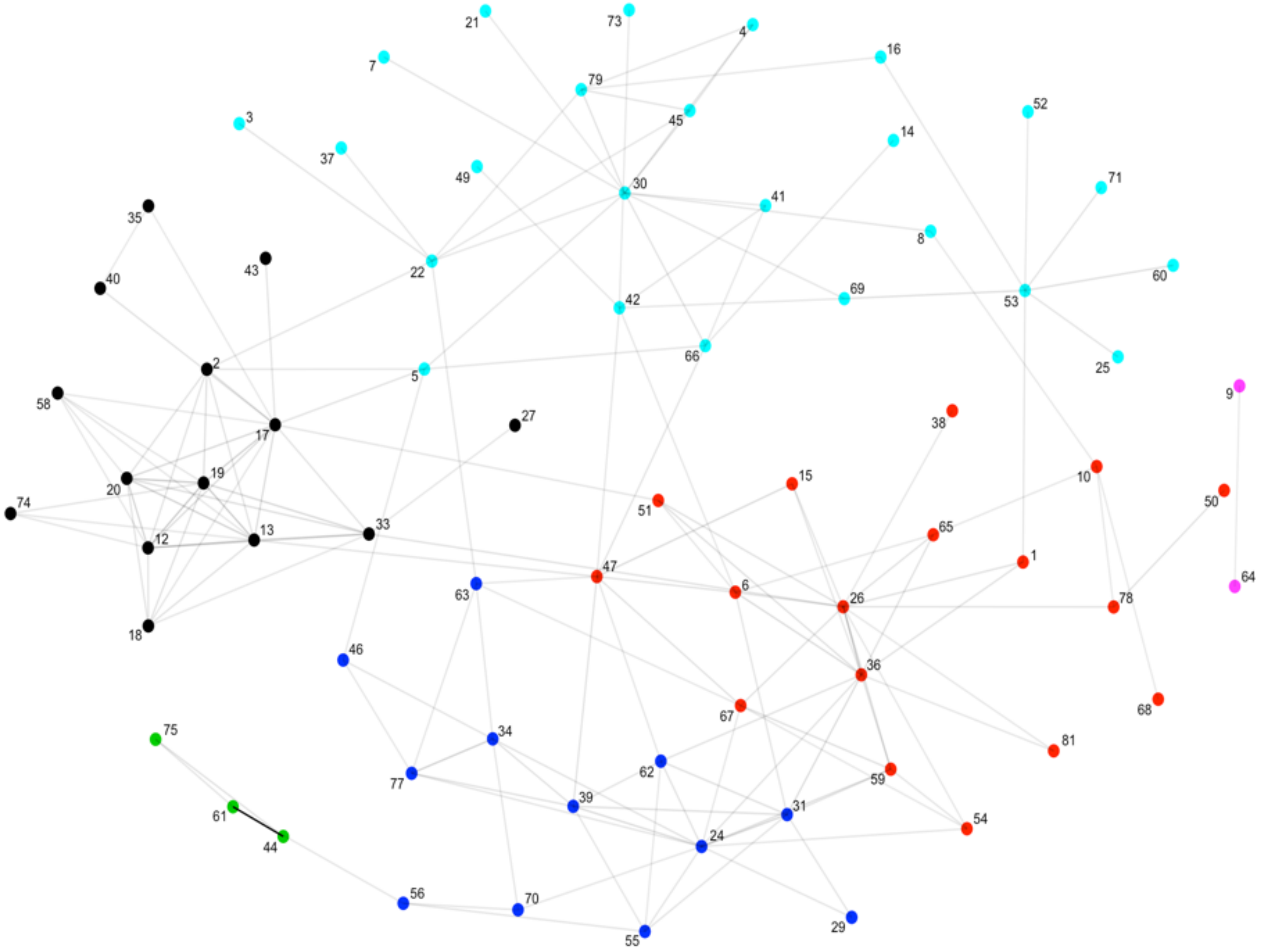
Depression Army



Forums
and Blogs

Text Network Analysis

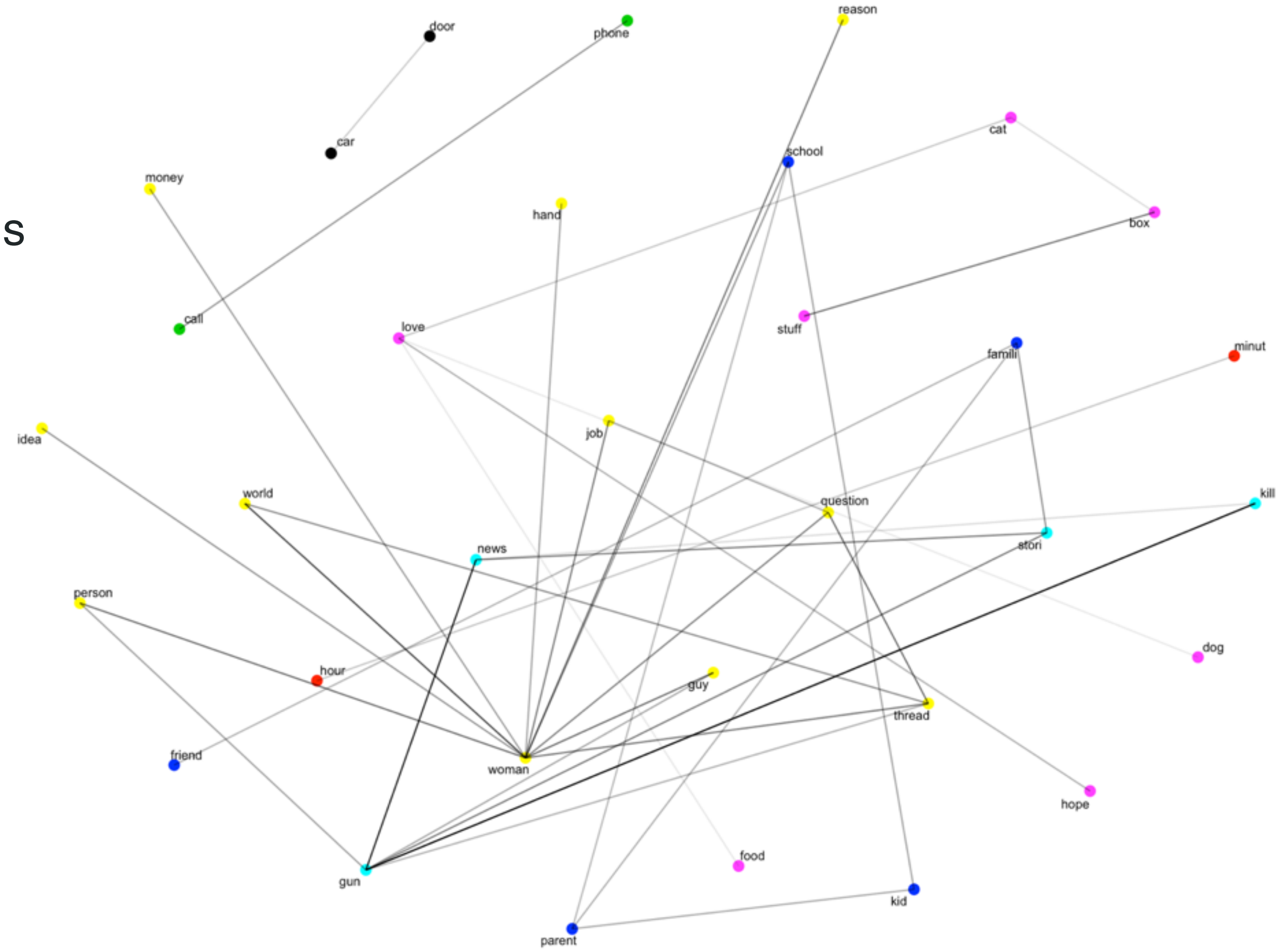
Depression Army



Forums
and Blogs

Text Network Analysis

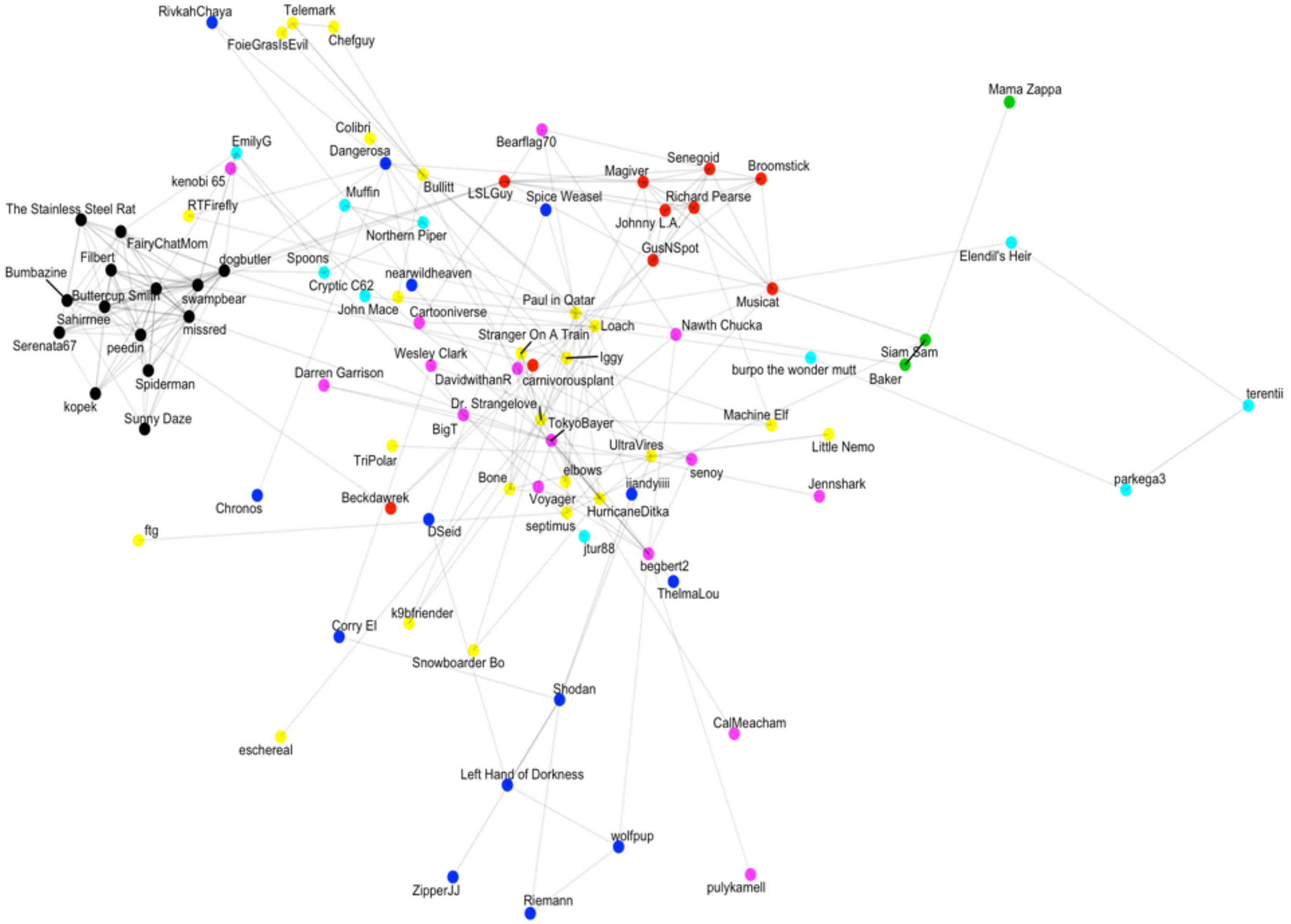
Straight Dope



Forums
and Blogs

Text Network Analysis

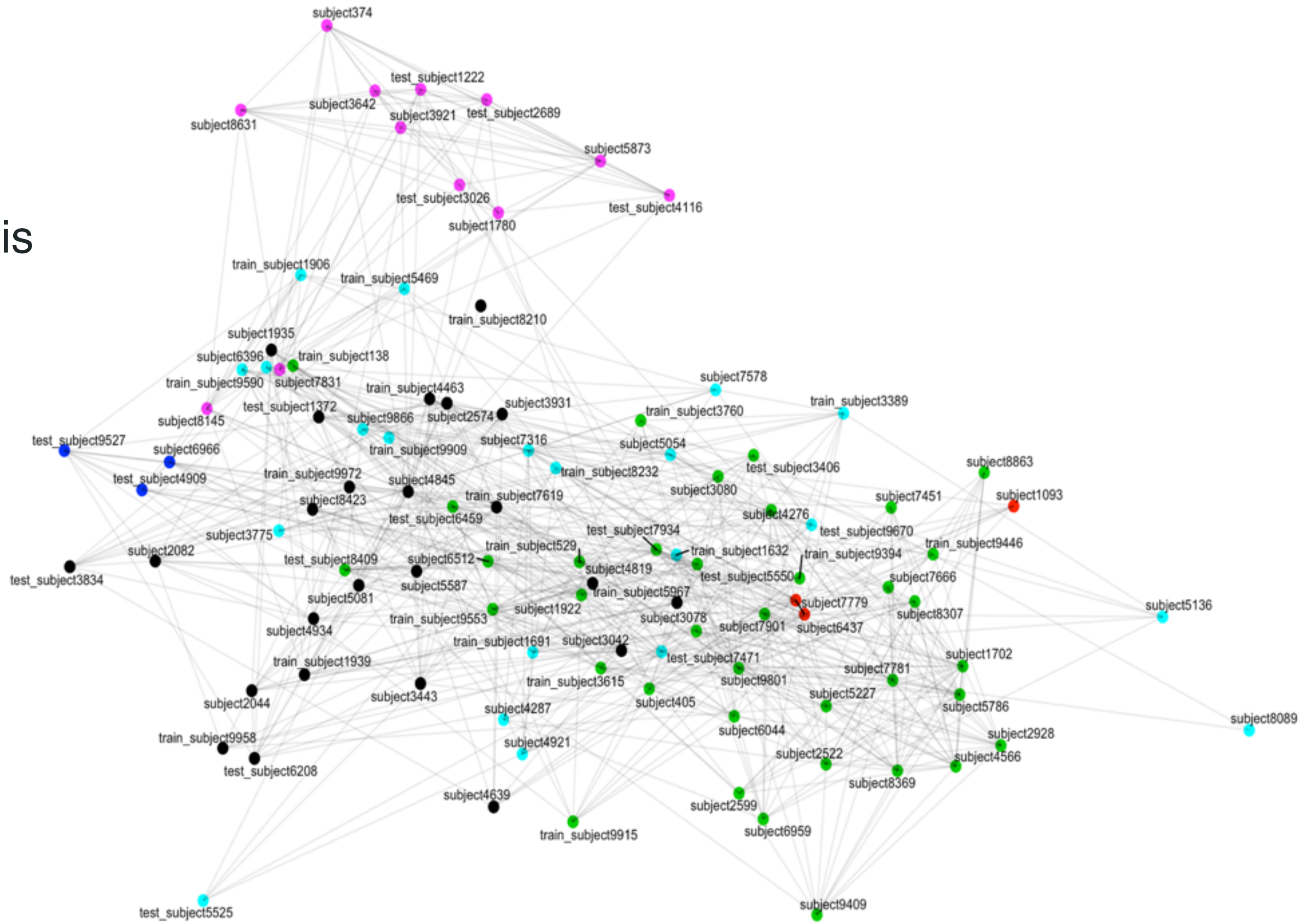
Straight Dope



Forums
and Blogs

Text Network Analysis

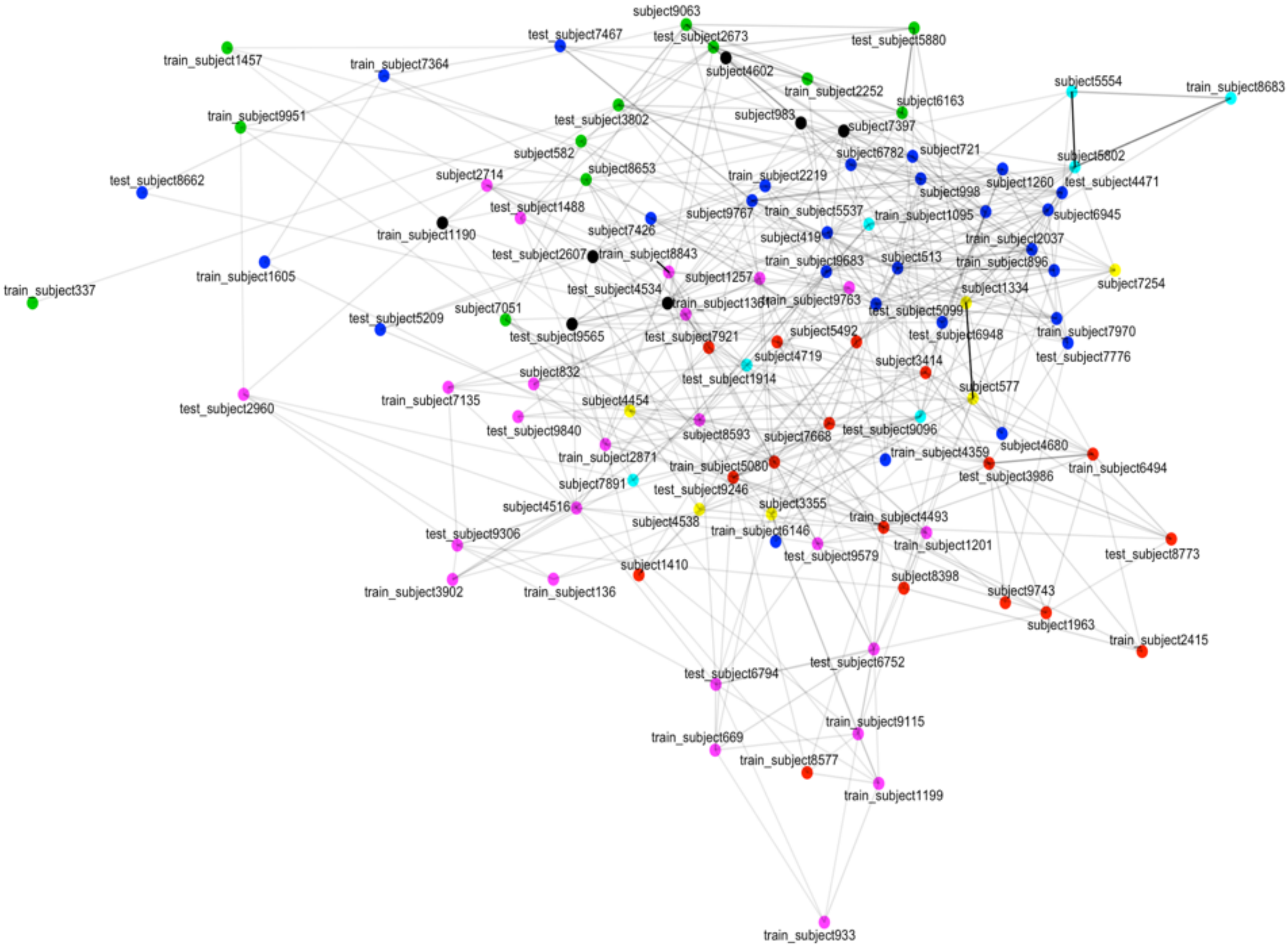
Early Risk: 0



Forums
and Blogs

Text Network Analysis

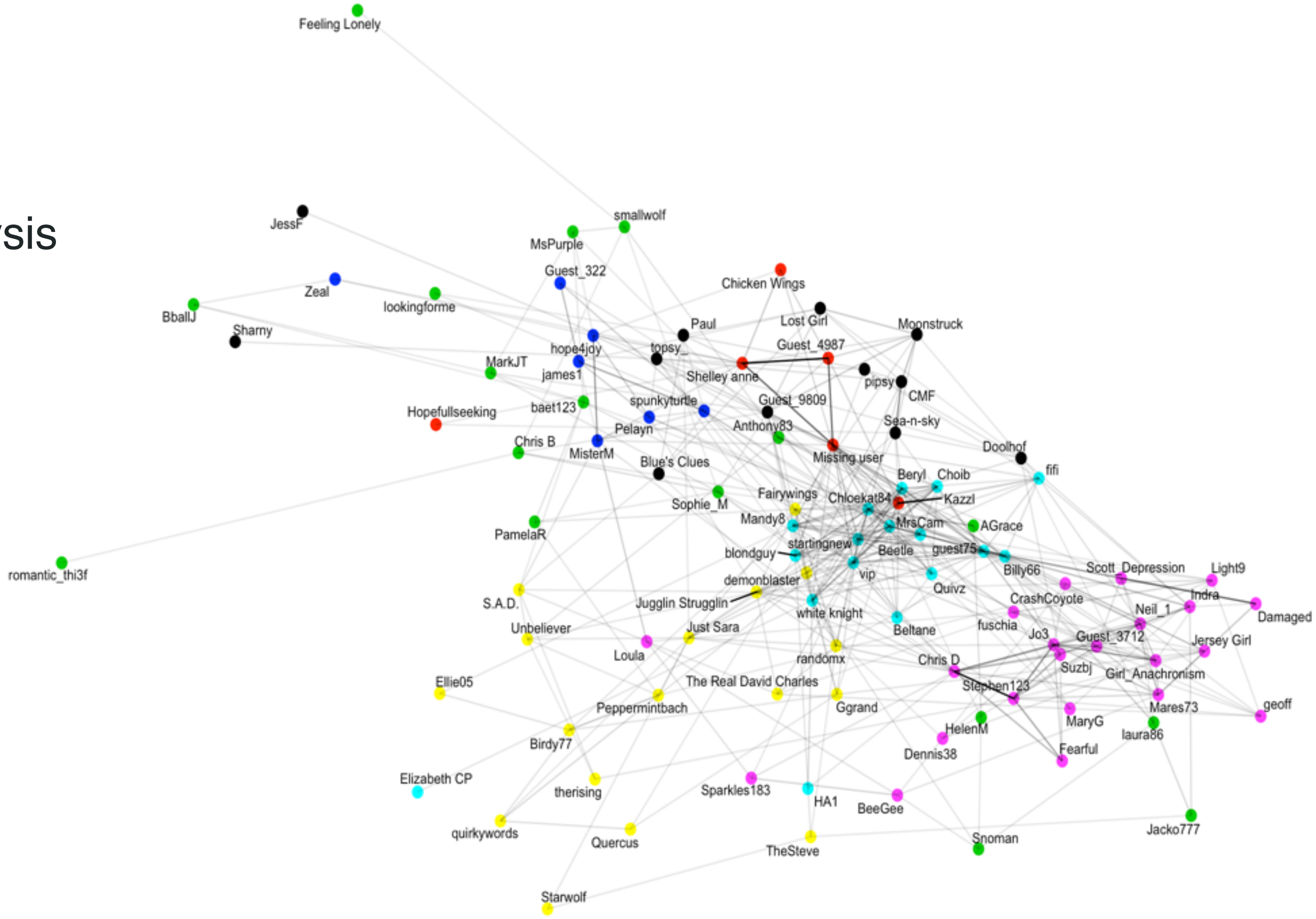
Early Risk: 1



Forums
and Blogs

Text Network Analysis

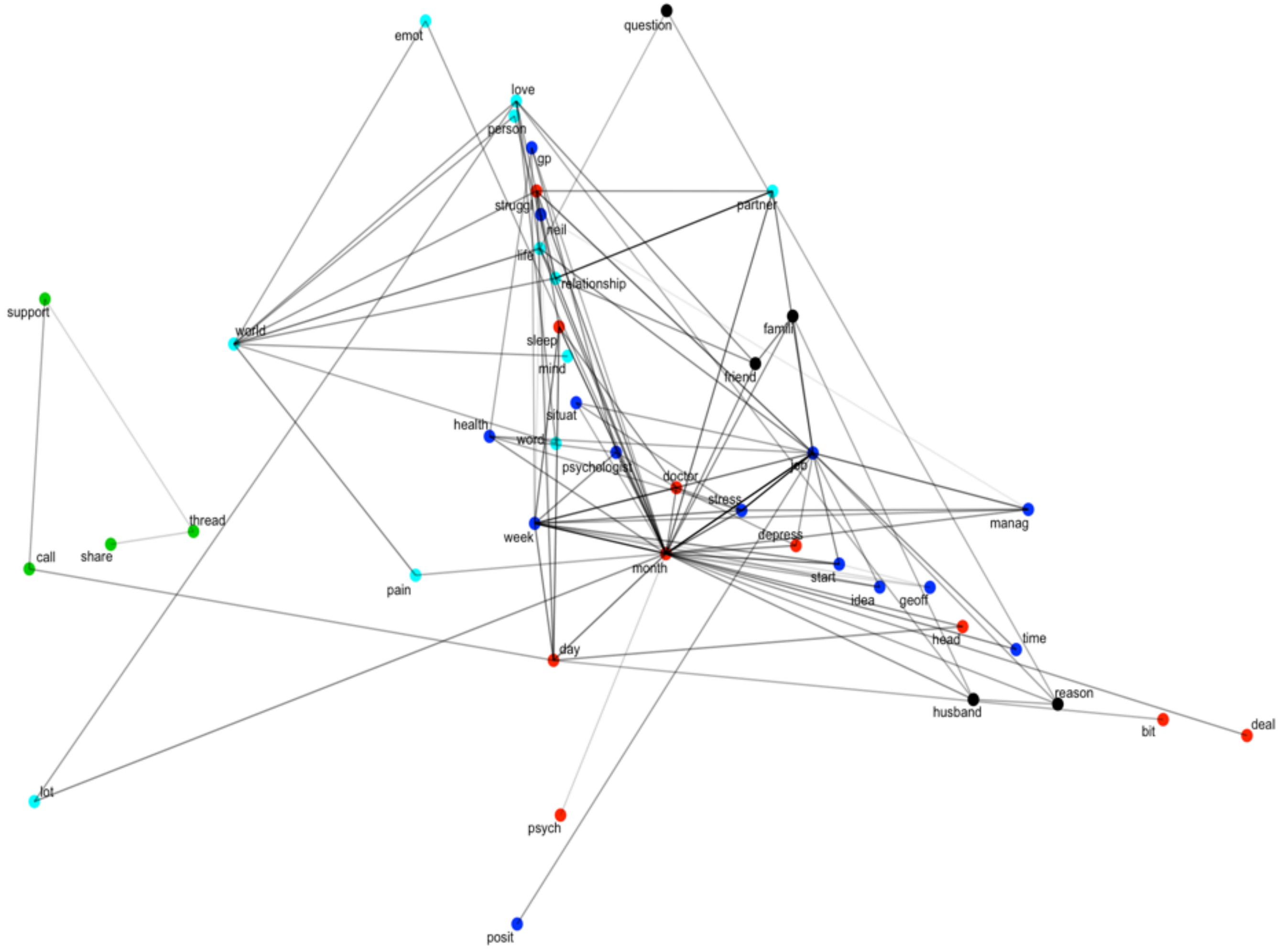
Beyond Blue



Forums
and Blogs

Text Network Analysis

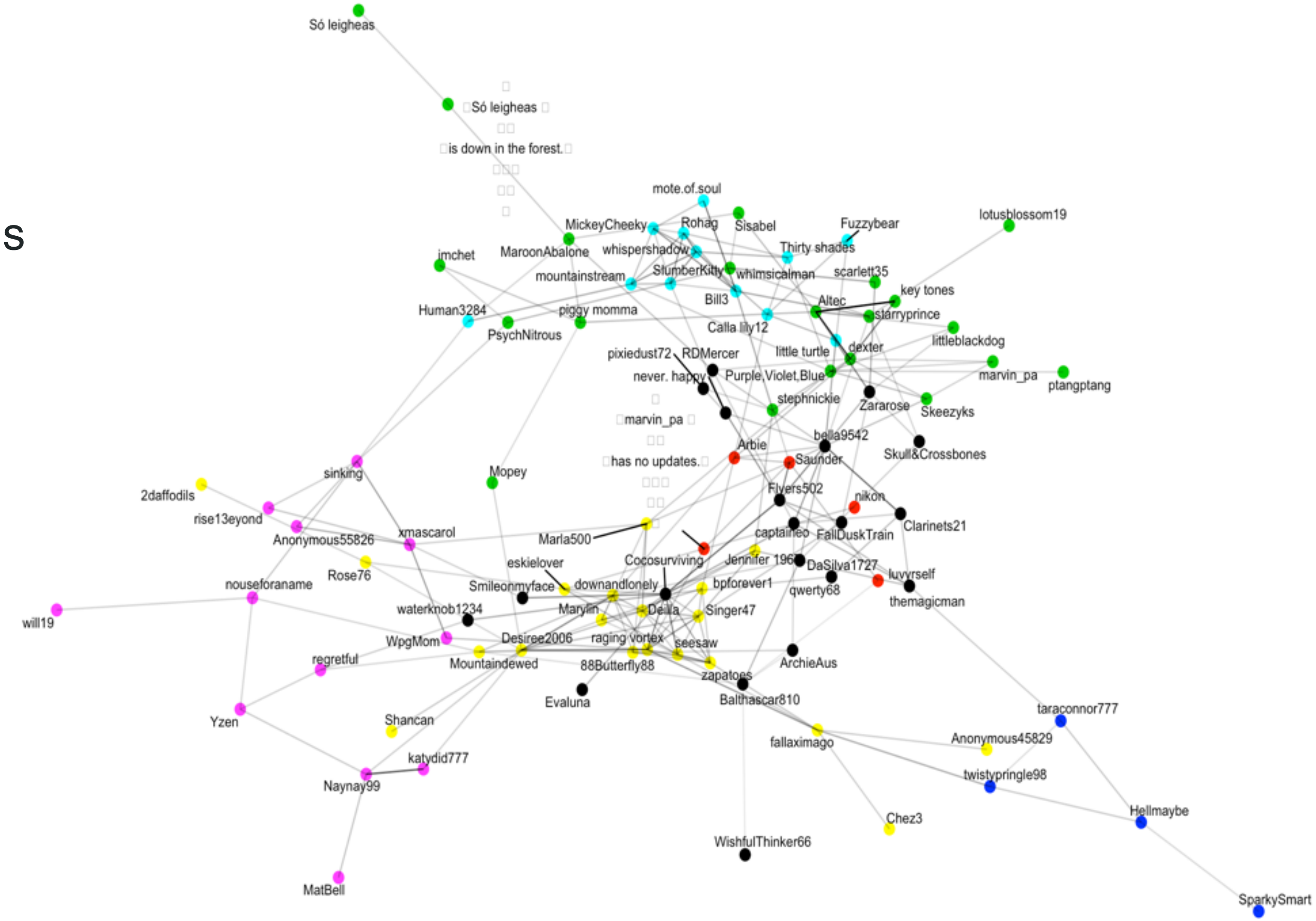
Beyond Blue



Forums
and Blogs

Text Network Analysis

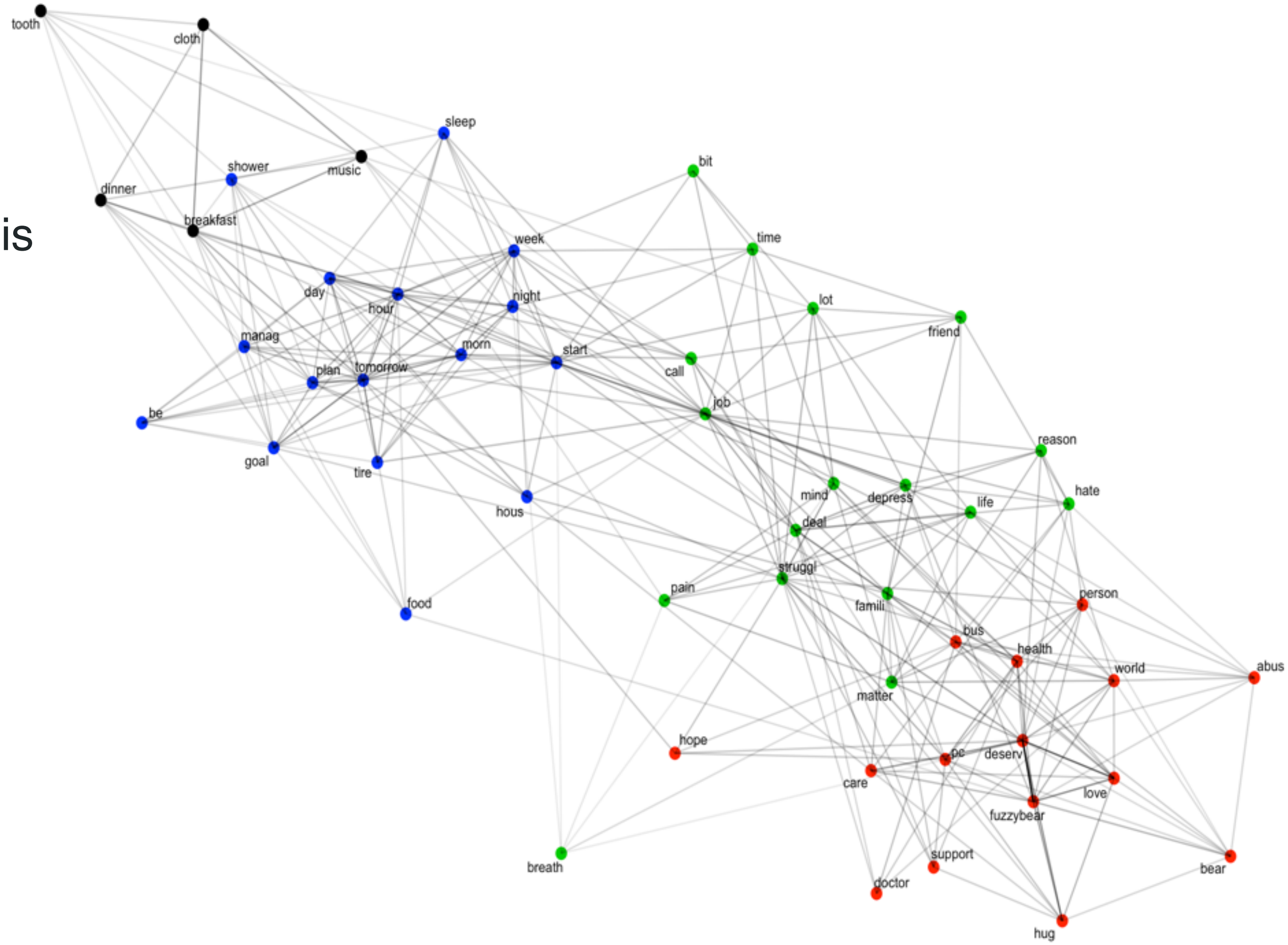
Psychcentral



Forums
and Blogs

Text Network Analysis

Psychcentral

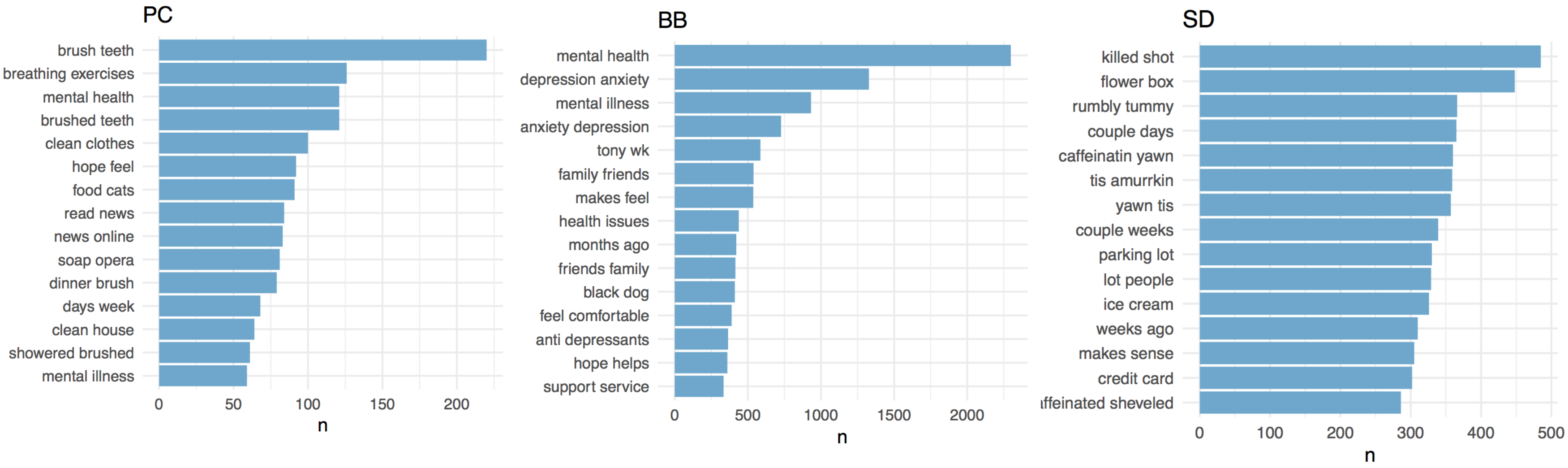


Forums

SHARED WORDS

Forums

FREQUENT BIGRAMS



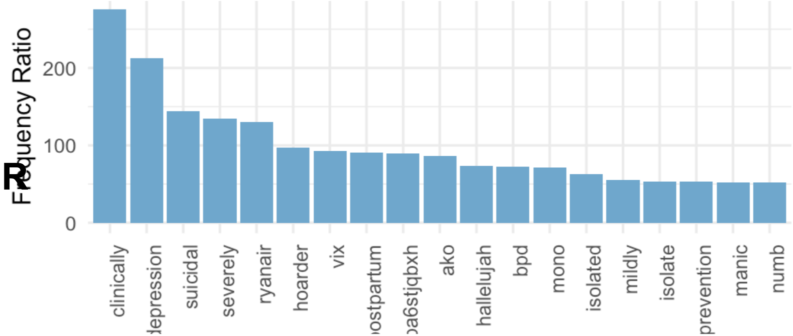
Platform Comparisons

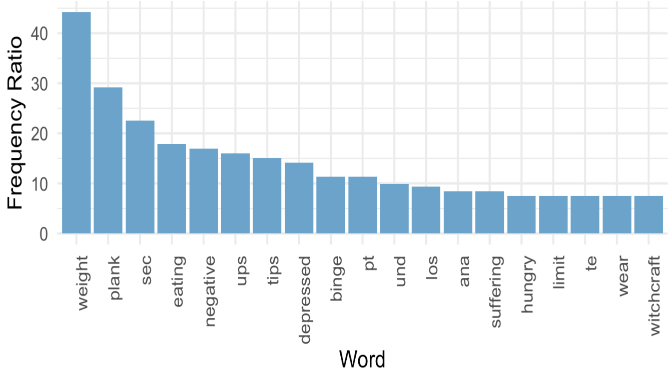
Dictionary-Based Analysis: Relative Frequencies

RATIO: DEPRESSED / RANDOM

WORDS MORE LIKELY TO BE IN 'DEPRESSED' SAMPLE

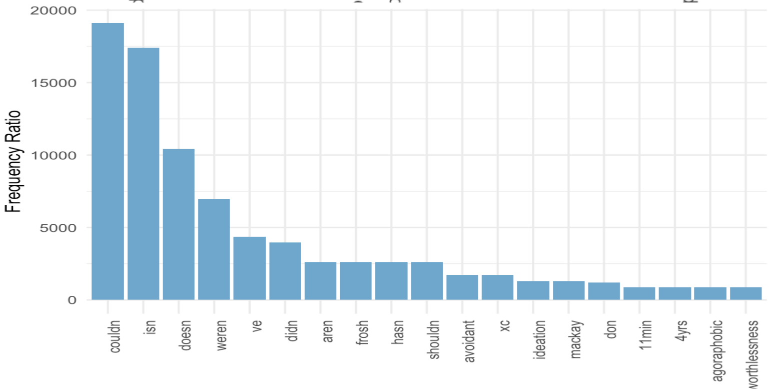
TWITTER

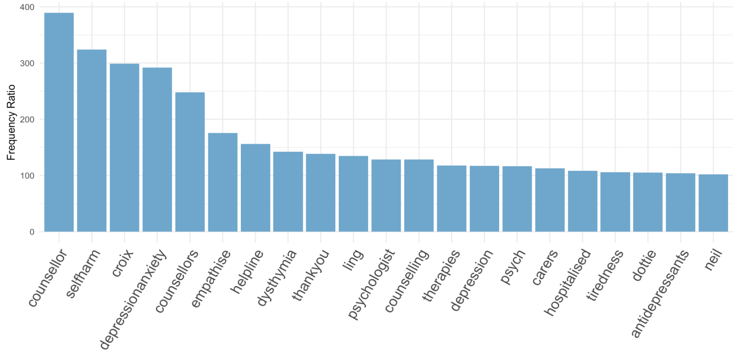




TUMBLR

REDDIT





FORUMS

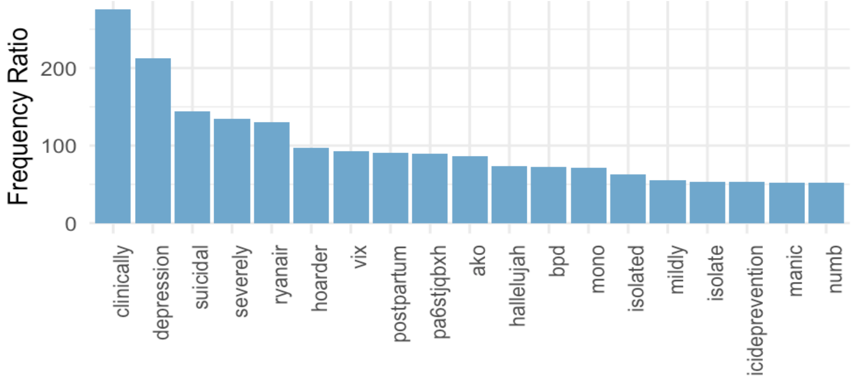
Dictionary-Based Analysis: Relative Frequencies

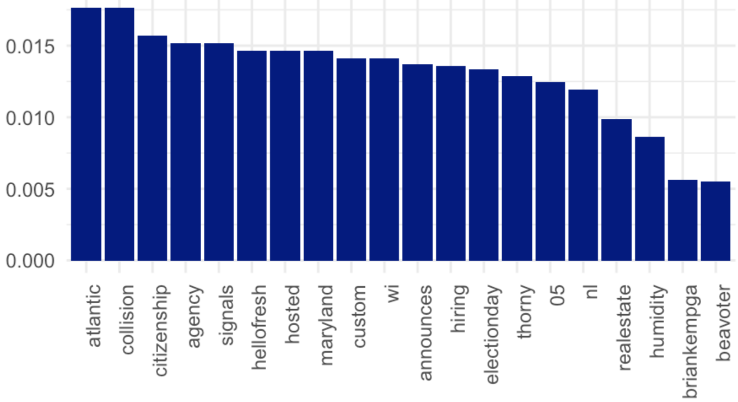
RATIO: DEPRESSED / RANDOM

WORDS MORE LIKELY TO BE IN 'DEPRESSED' SAMPLE

WORDS MORE LIKELY TO BE IN RANDOM SAMPLE

TWITTER





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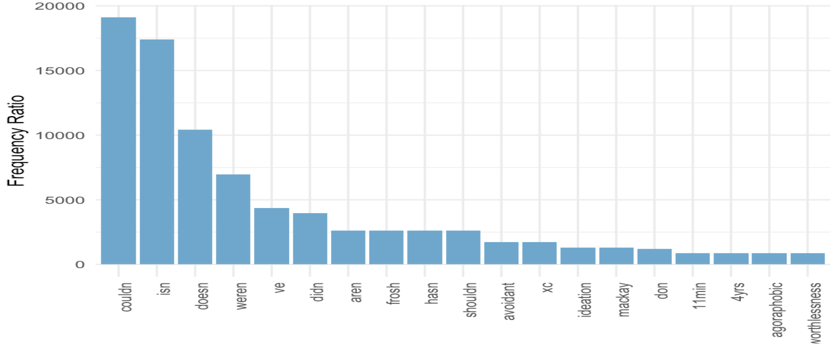
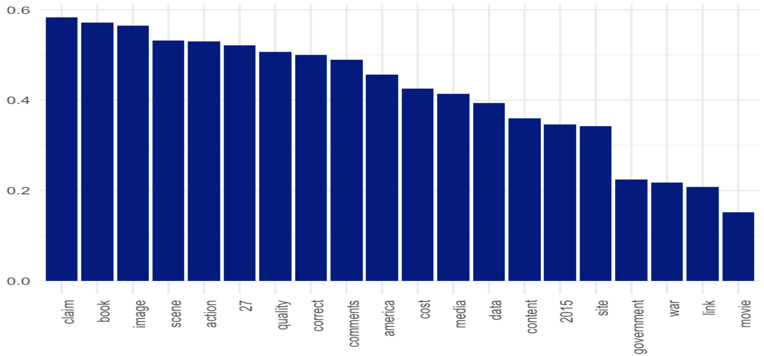




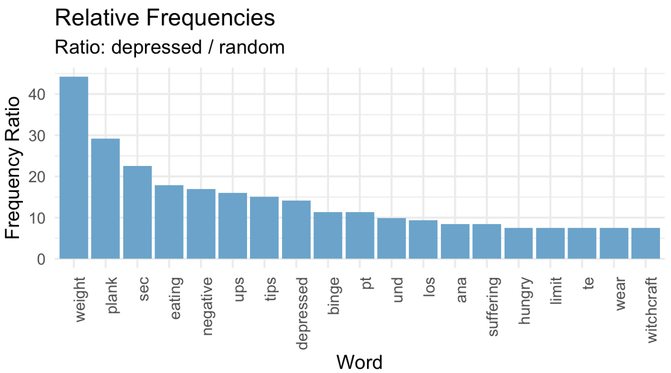
Dictionary-Based Analysis: Relative Frequencies

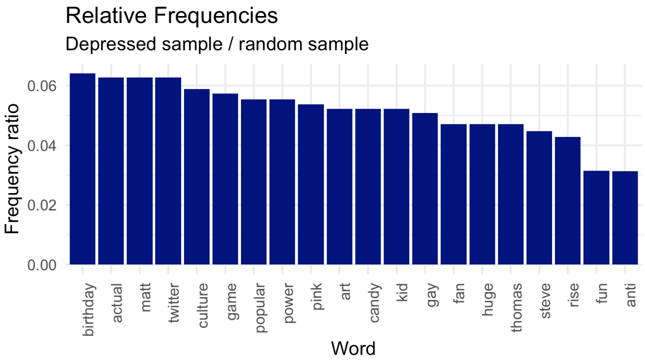
RATIO: DEPRESSED / RANDOM

WORDS MORE LIKELY TO BE IN ‘DEPRESSED’ SAMPLE

WORDS MORE LIKELY TO BE IN RANDOM SAMPLE

TUMBLR





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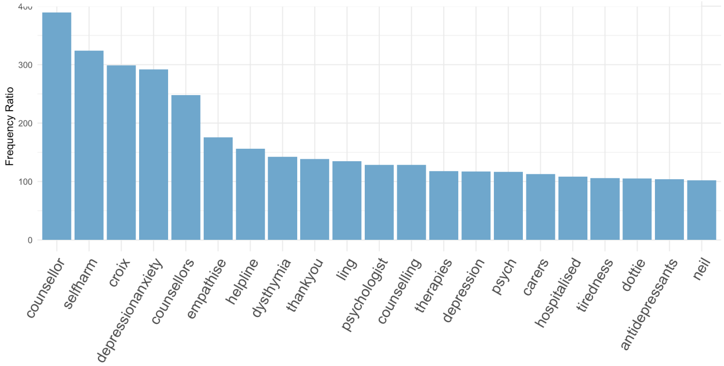
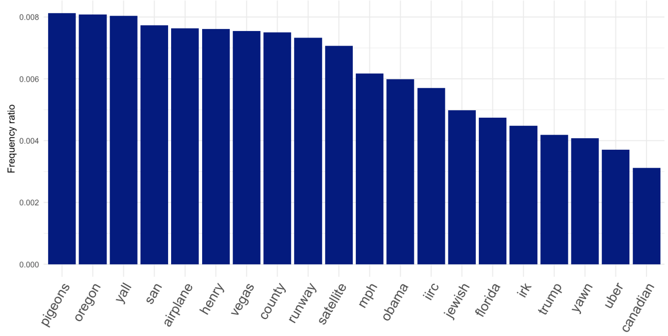




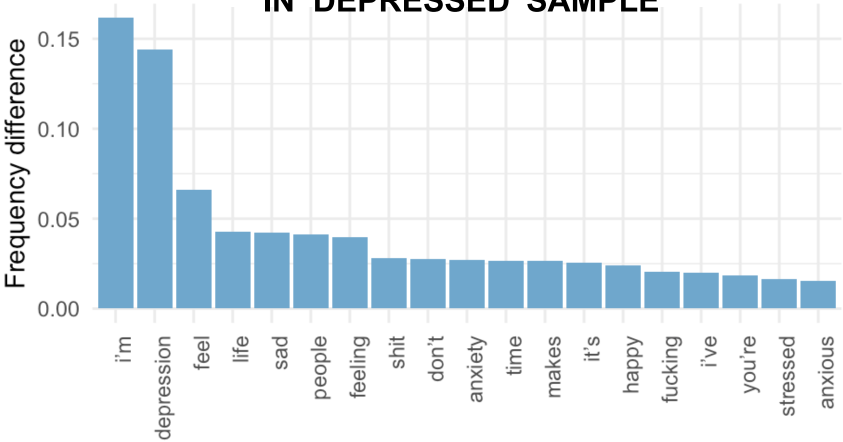
Dictionary-Based Analysis: Relative Frequencies

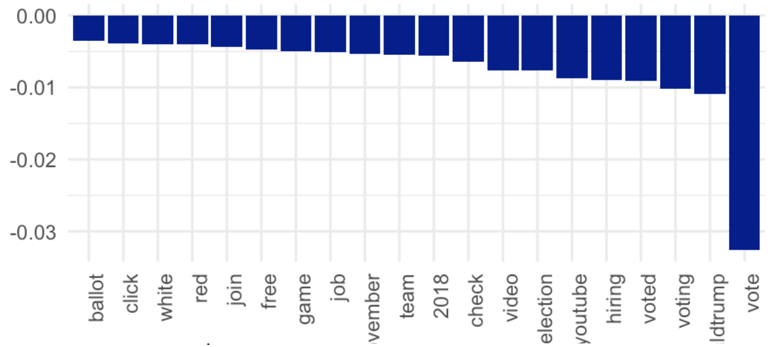
DIFFERENCE: DEPRESSED - RANDOM

WORDS MORE LIKELY TO BE IN 'DEPRESSED' SAMPLE

WORDS MORE LIKELY TO BE IN RANDOM SAMPLE

TWITTER





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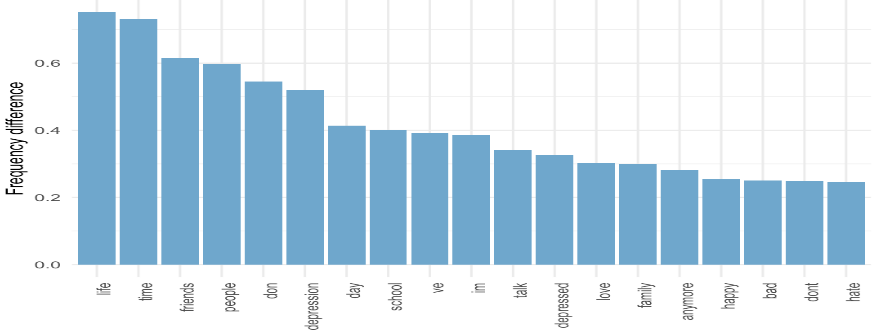
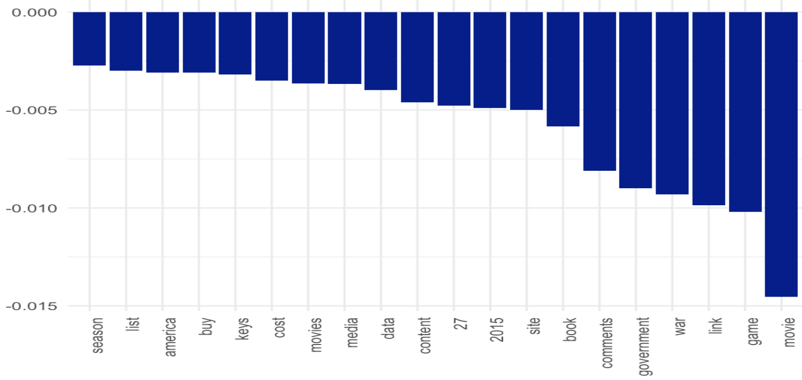




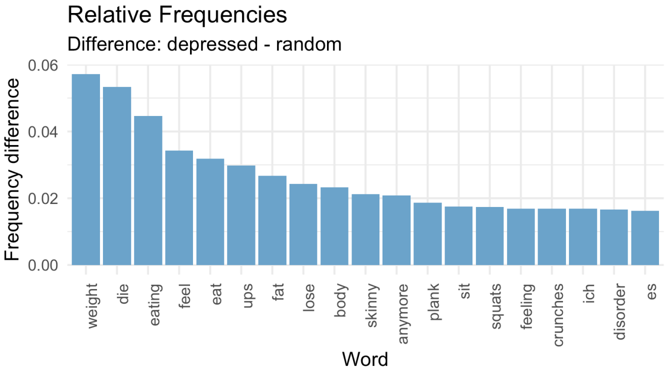
Dictionary-Based Analysis: Relative Frequencies

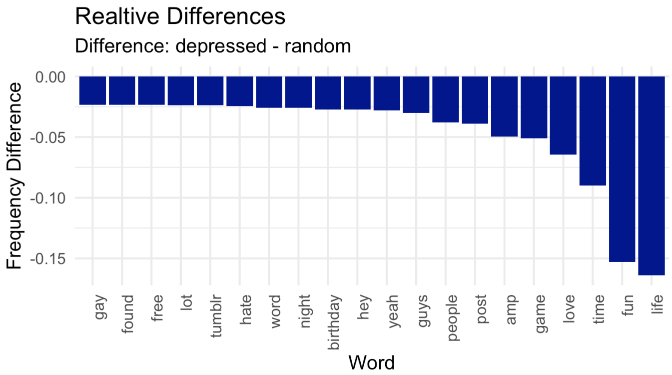
DIFFERENCE: DEPRESSED - RANDOM

WORDS MORE LIKELY TO BE IN 'DEPRESSED' SAMPLE

WORDS MORE LIKELY TO BE IN RANDOM SAMPLE

TUMBLR





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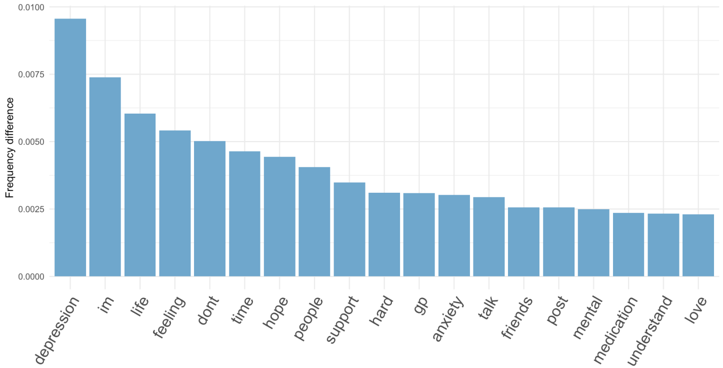
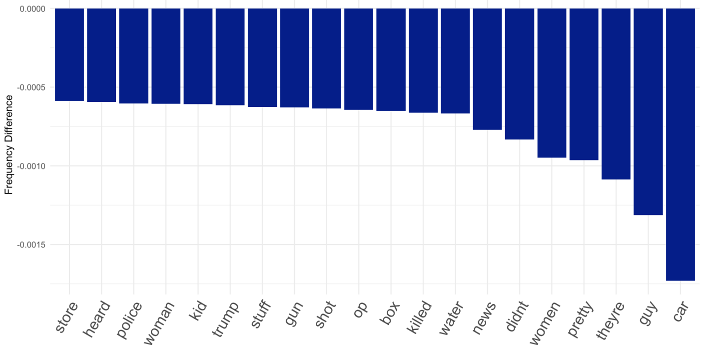
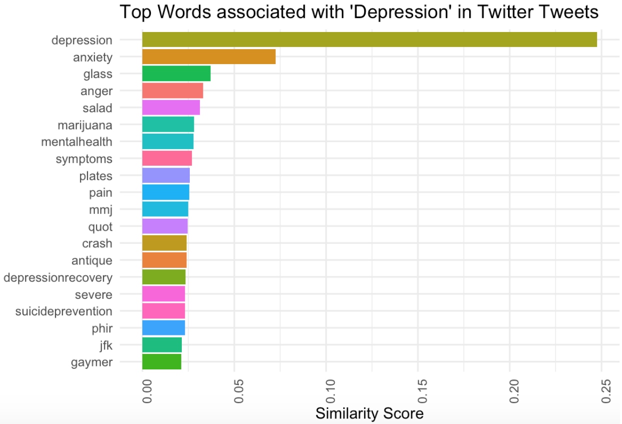




Word2vec

SIMILARITY: DEPRESSION

TWITTER



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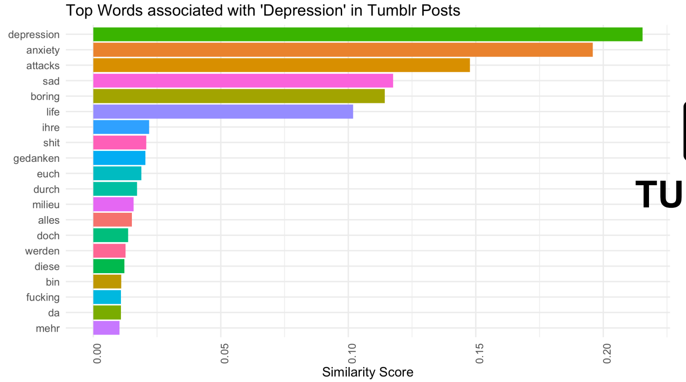

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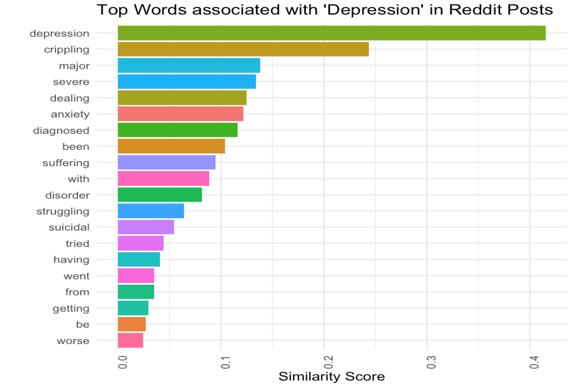

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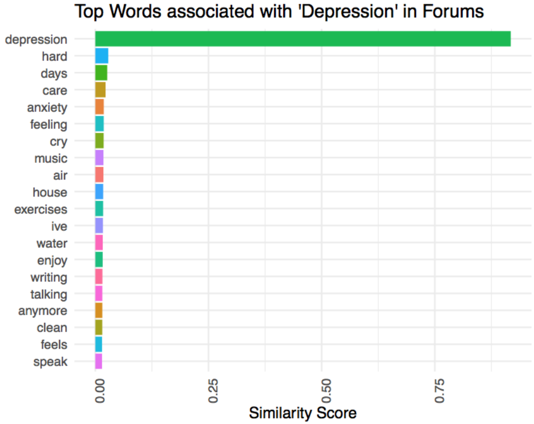
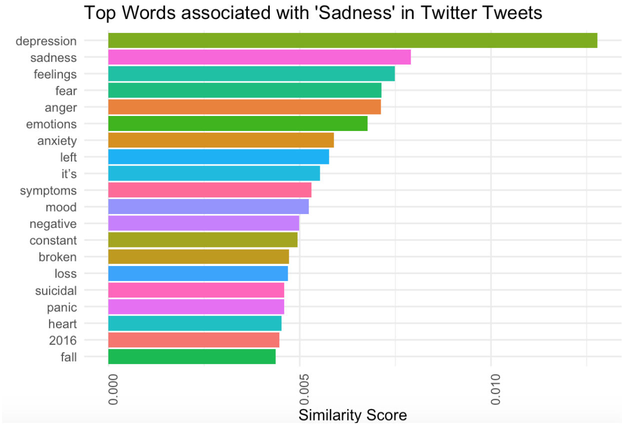


Word2vec

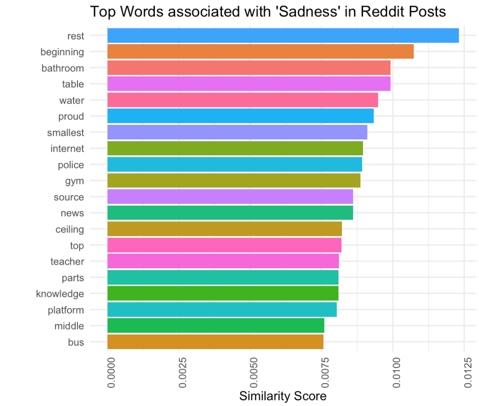
SIMILARITY: SADNESS

TWITTER



In tumblr post, there is no sadness after stemming…
Does it necessary to include sad & sadness at the same time?

TUMBLR



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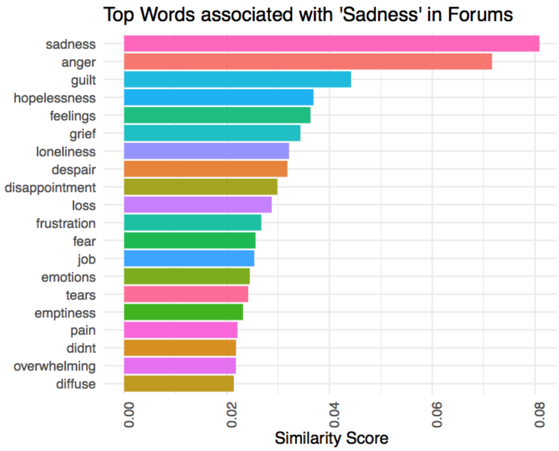
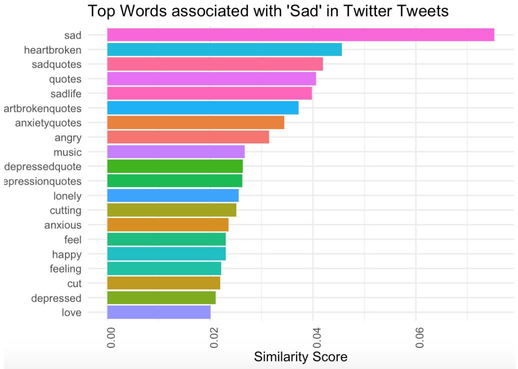


FORUMS

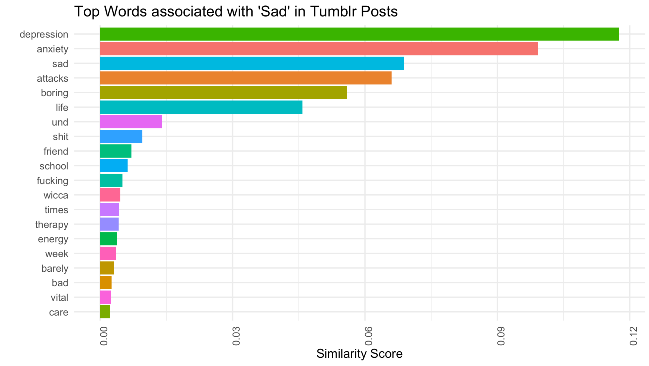
Word2vec

SIMILARITY: SAD

TWITTER



TUMBLR



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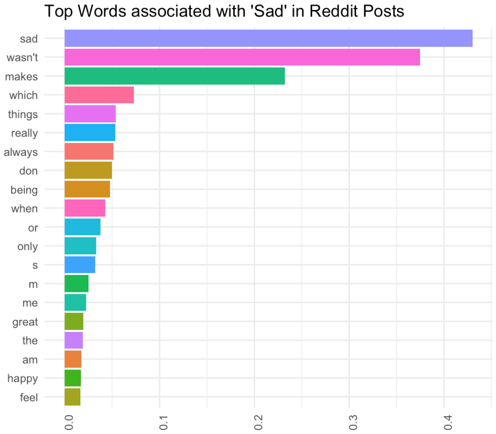

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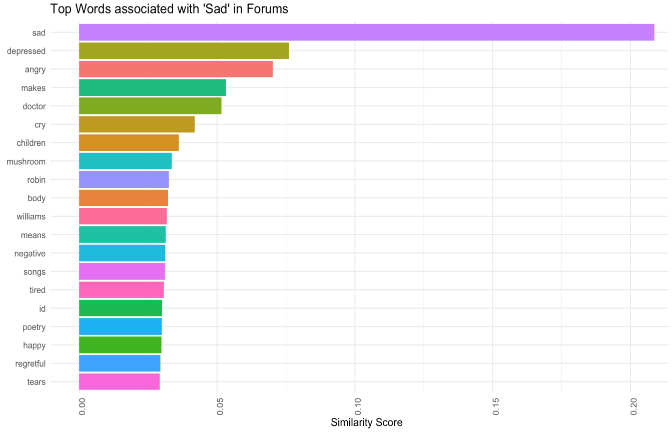
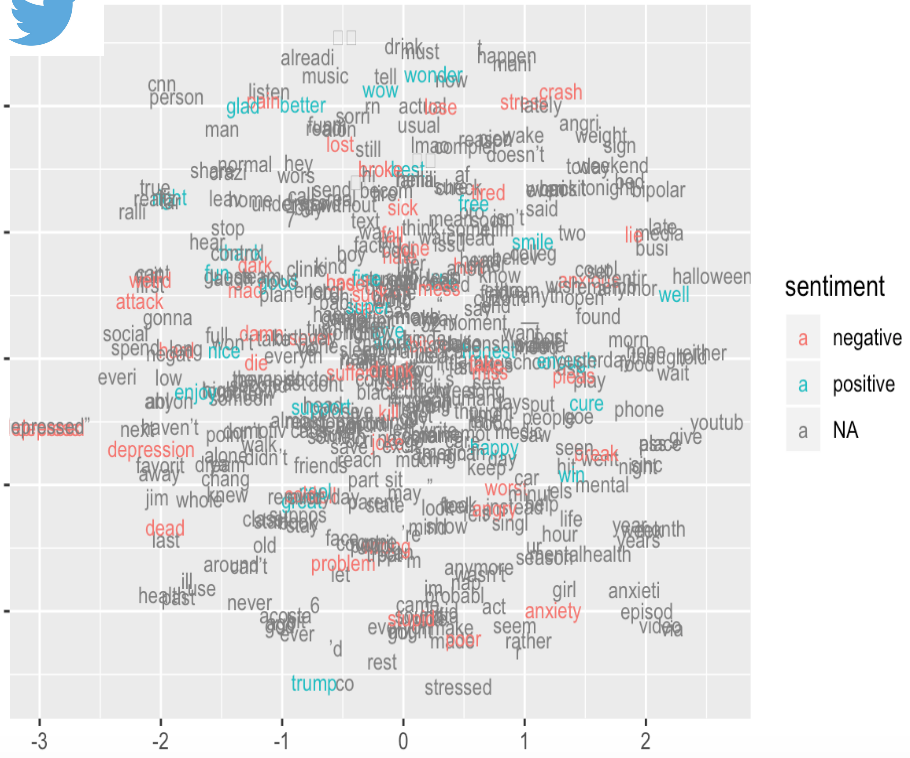
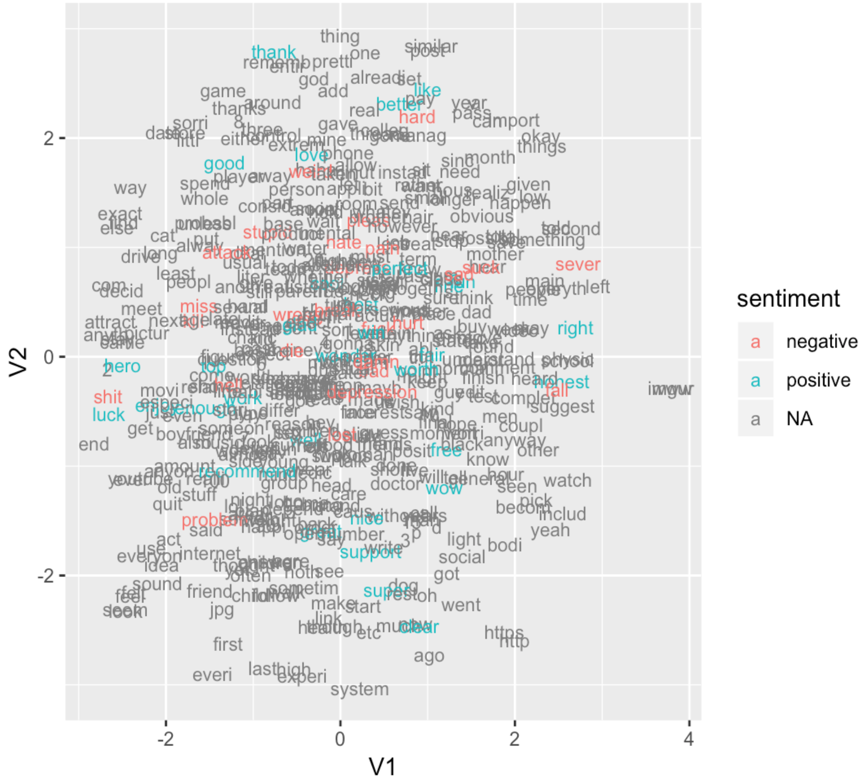


Embeddings

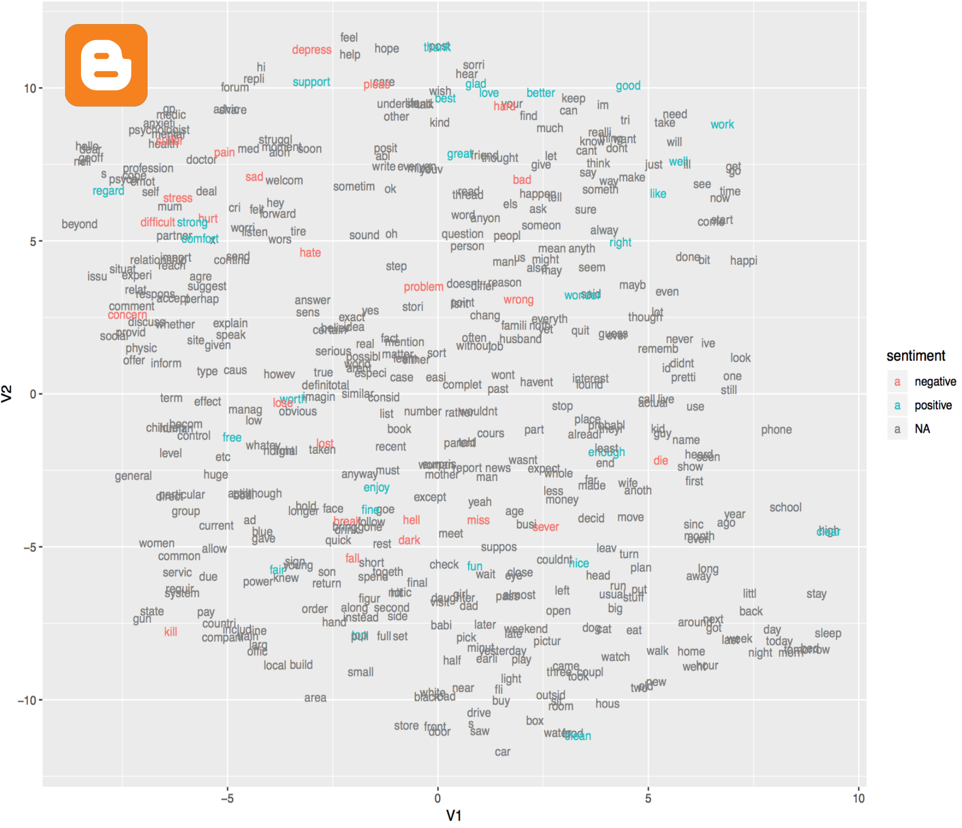
TSNE PLOT WITH 500 TOP WORDS

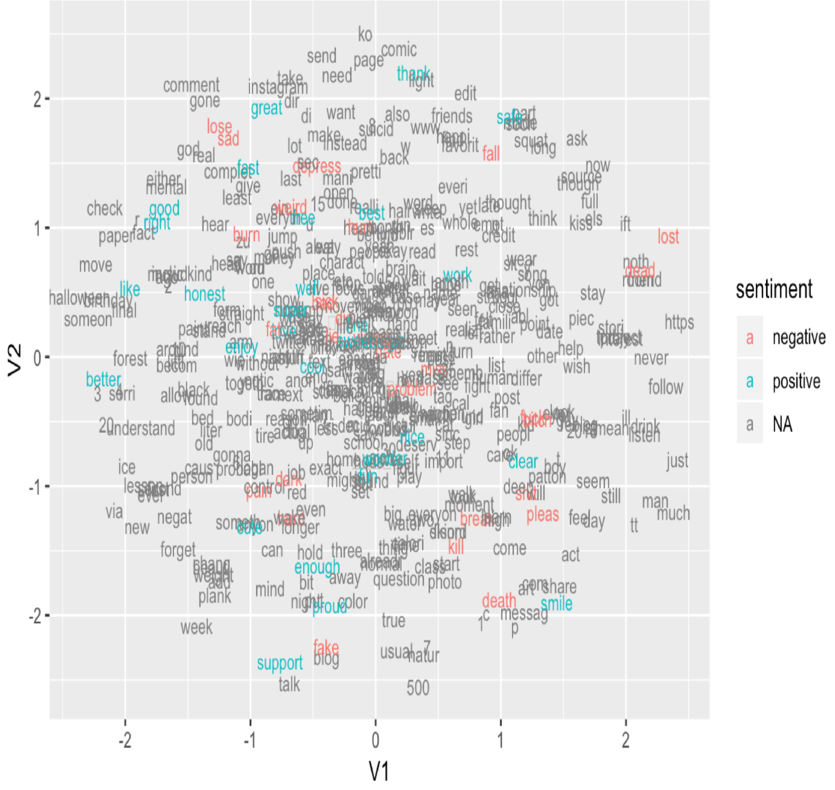




Embeddings

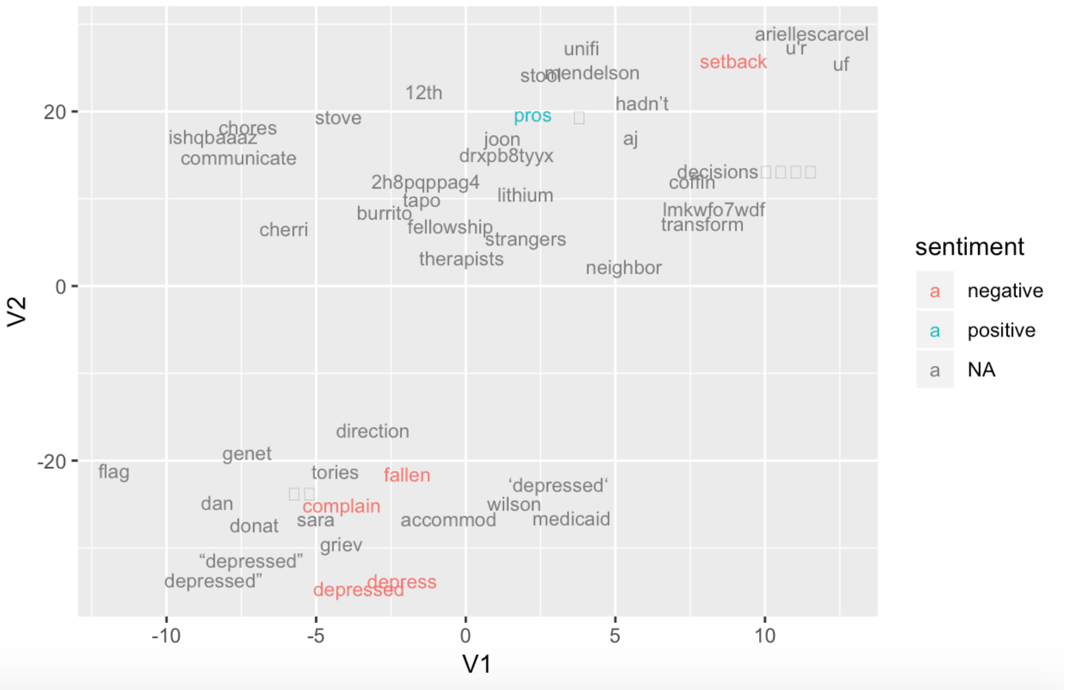
TSNE PLOT WITH 500 TOP WORDS





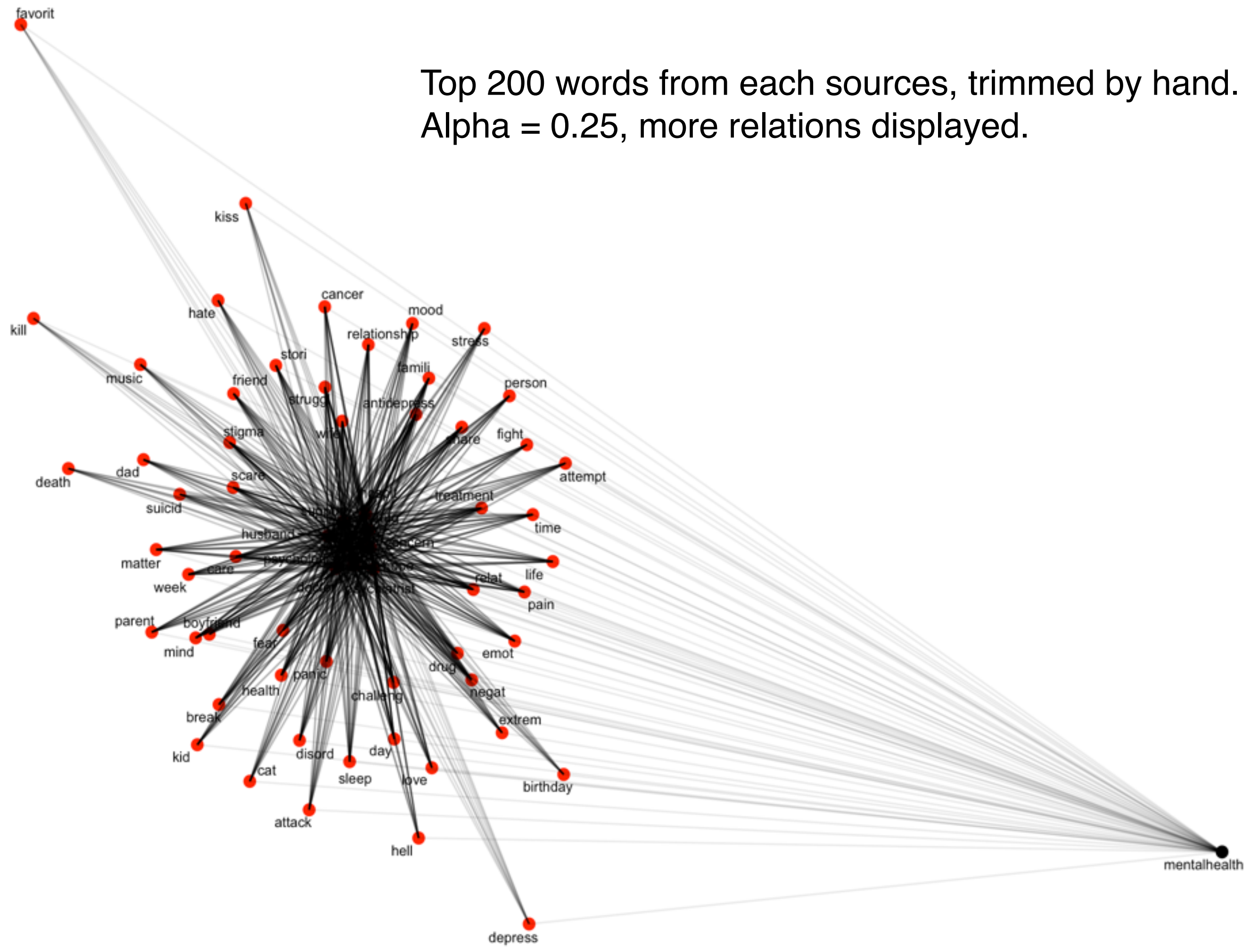
Embeddings

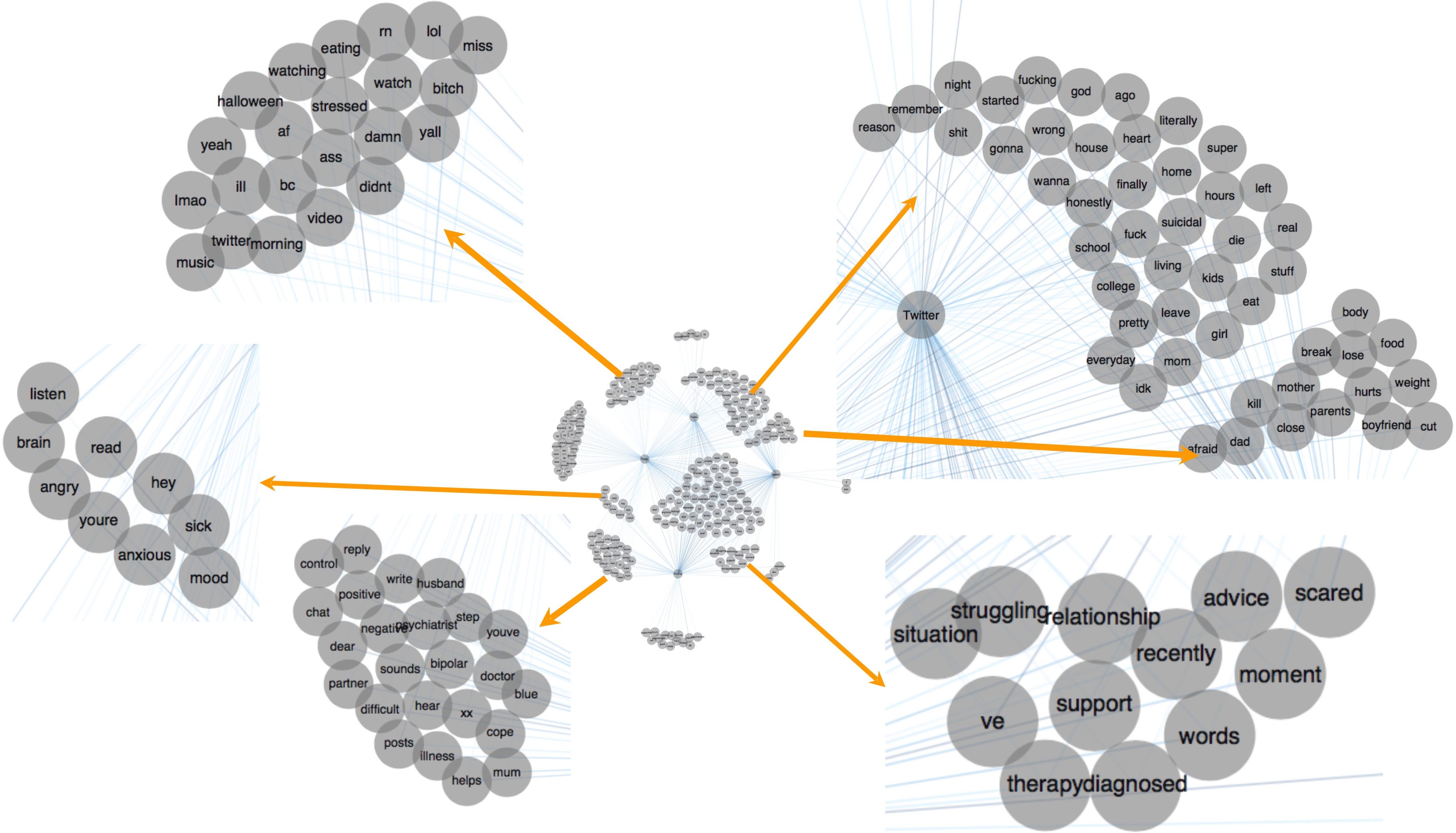
TSNE PLOT WITH 50 WORDS SIMILAR TO DEPRESS



Combined Network: Words

Top 200 words from each sources, trimmed by hand.
Alpha = 0.25, more relations displayed.





rn
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watching
watch
bitch
halloween
stressed
yeah
af
damn
yall
ass
lmao
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bc
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video
twitter
morning
music
night
fucking
remember
started
god
ago
reason
shit
wrong
heart
literally
gonna
house
super
home
wanna
finally
left
honestly
hours
suicidal
real
fuck
school
die
living
kids
stuff
college
Twitter
eat
leave
pretty
girl
body
everyday
mom
food
break
lose
idk
weight
mother
hurts
kill
parents
boyfriend
close
cut
dad
afraid
listen
brain
read
angry
hey
youre
sick
anxious
mood
reply
control
write
husband
positive
chat
step
psychiatrist
negative
youve
dear
sounds
bipolar
doctor
partner
blue
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hear
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cope
posts
illness
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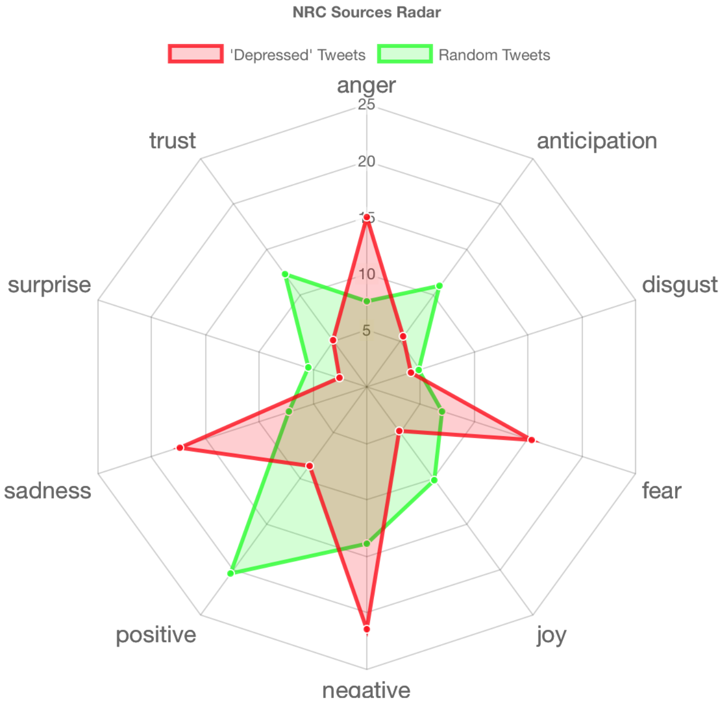
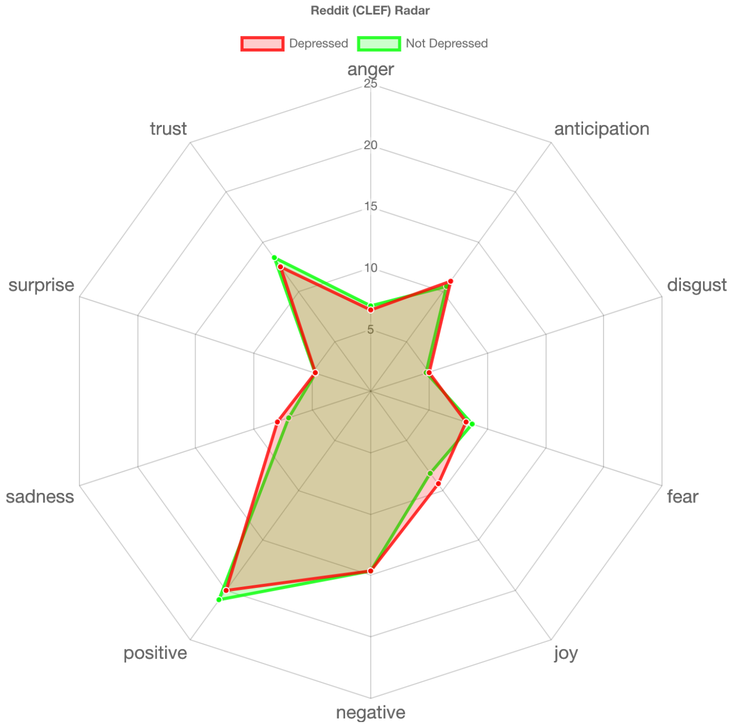
NCR Radar

TWITTER

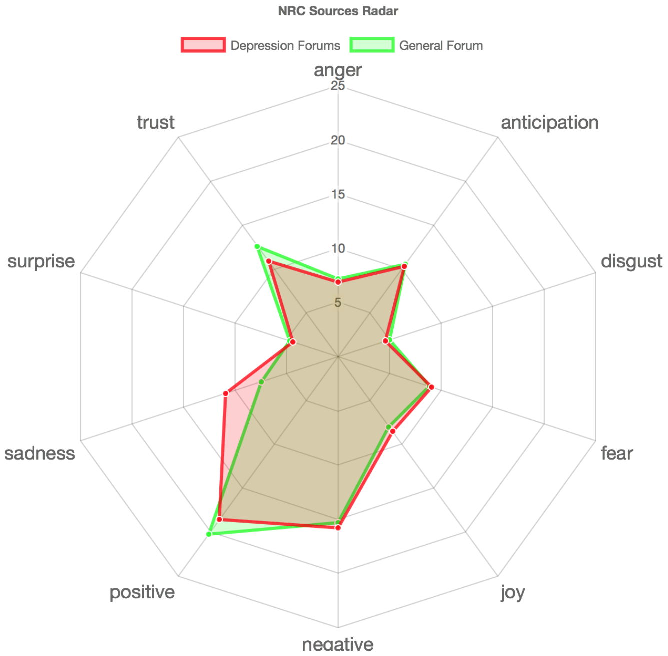


REDDIT

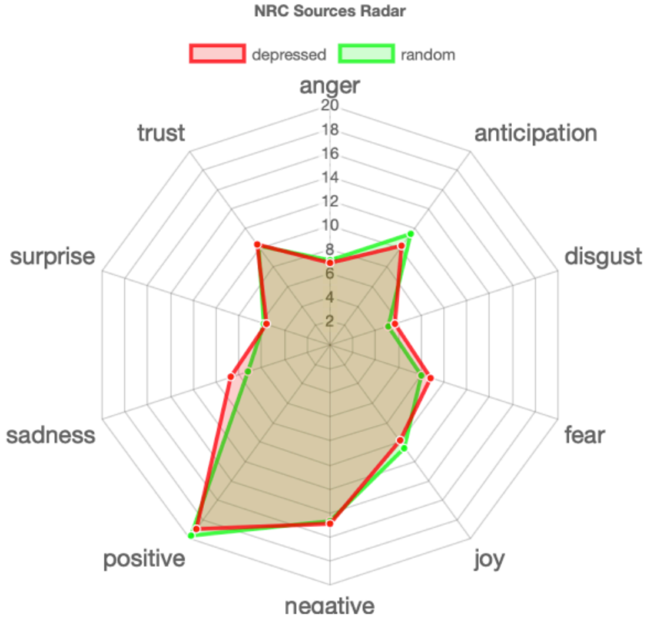


NCR Radar

FORUMS

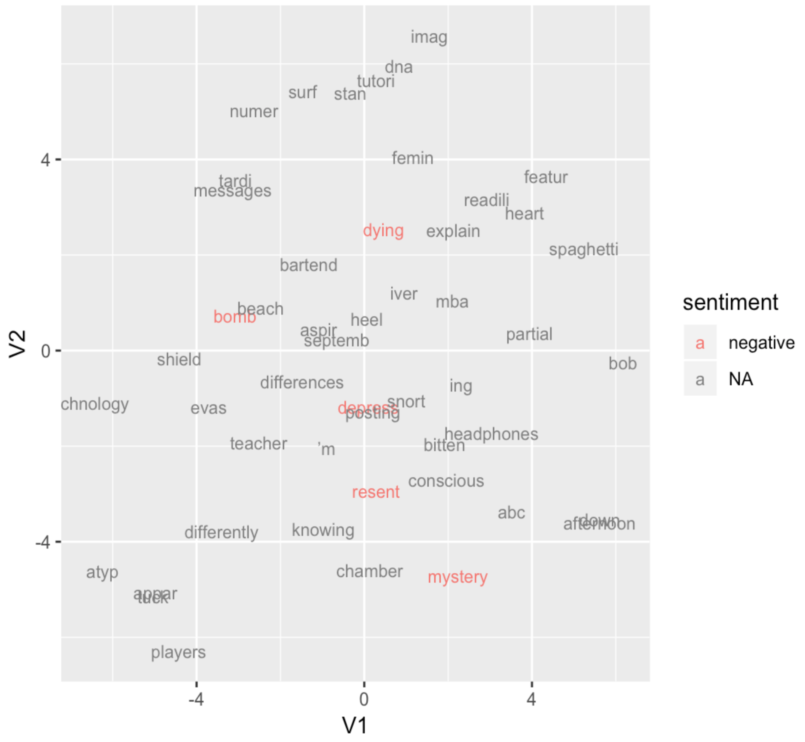


TUMBLR



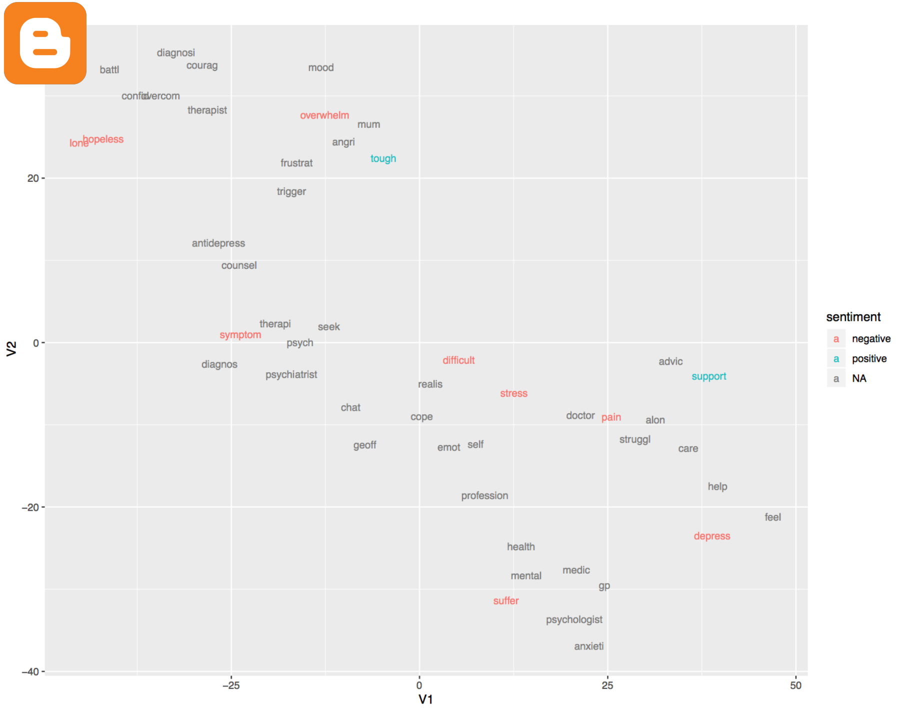
Embeddings

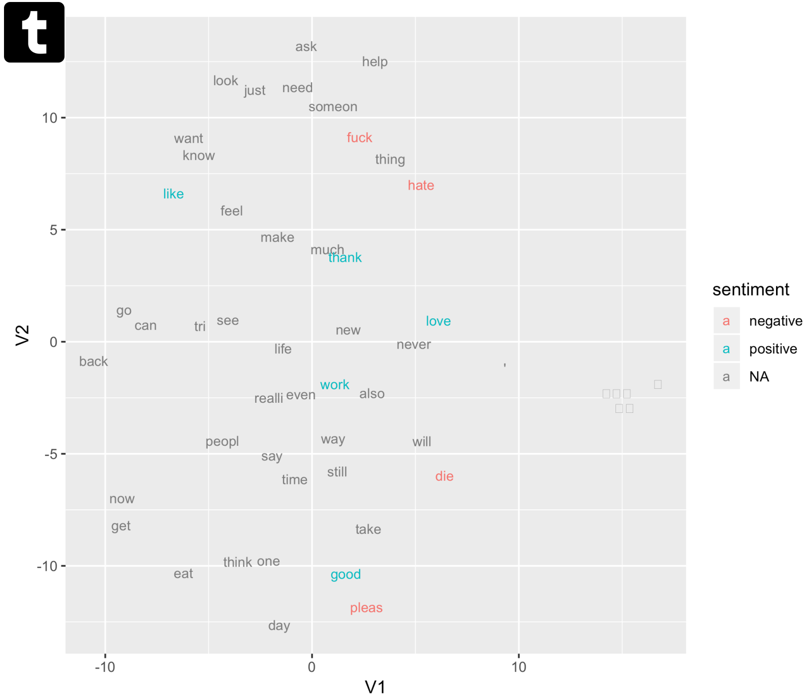
TSNE PLOT WITH 50 WORDS SIMILAR TO DEPRESS



Embeddings

TSNE PLOT WITH 50 WORDS SIMILAR TO DEPRESS

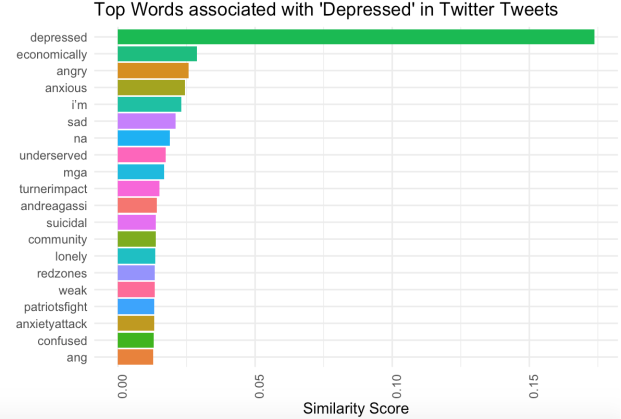




Word2vec

SIMILARITY: DEPRESSED

TWITTER



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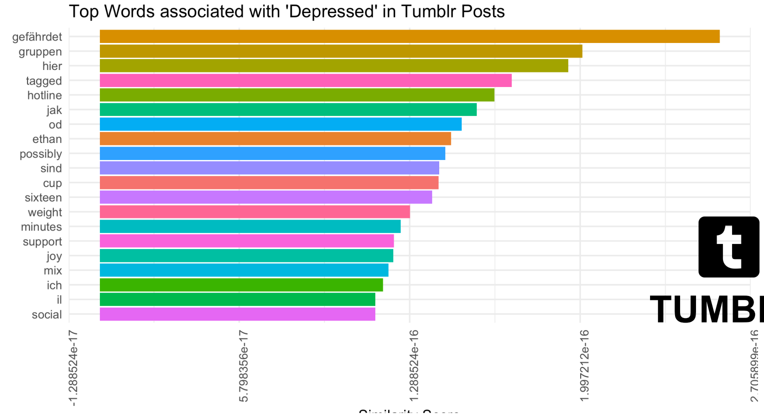

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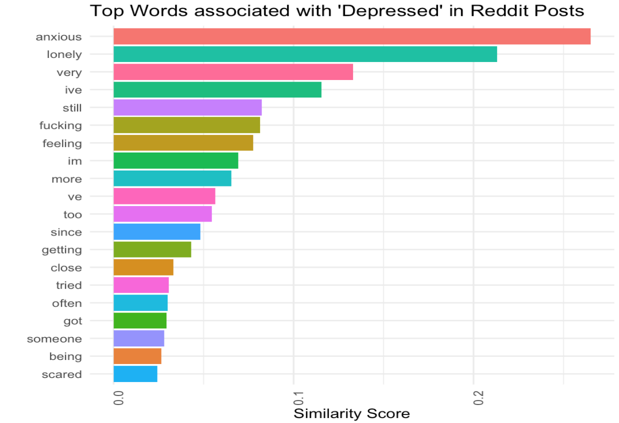
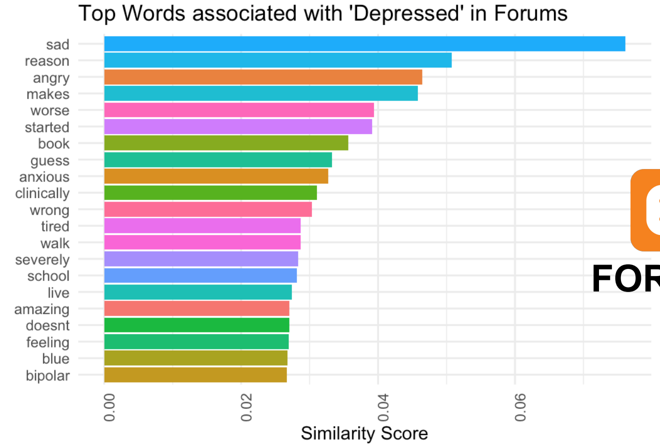


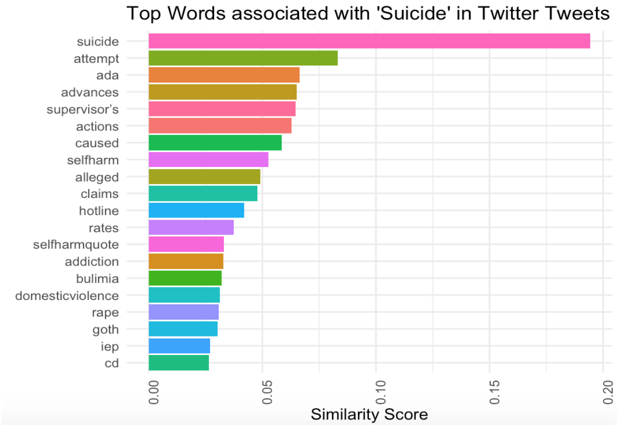
FORUMS



Word2vec

SIMILARITY: SUICIDE

TWITTER



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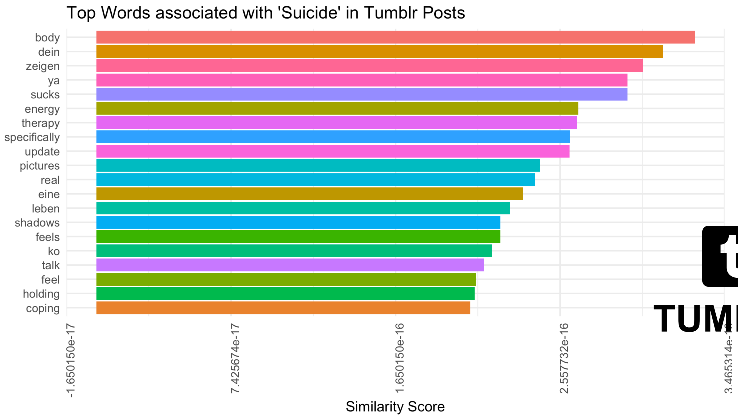

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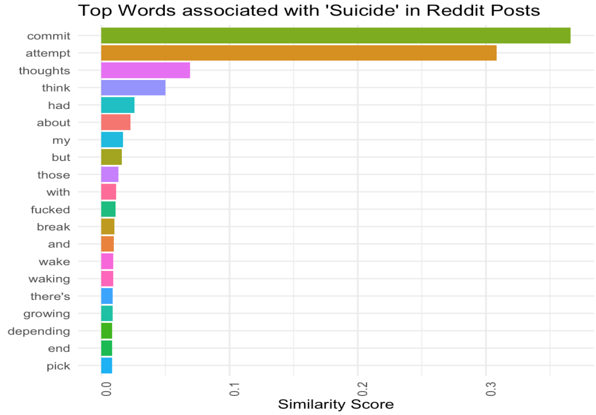
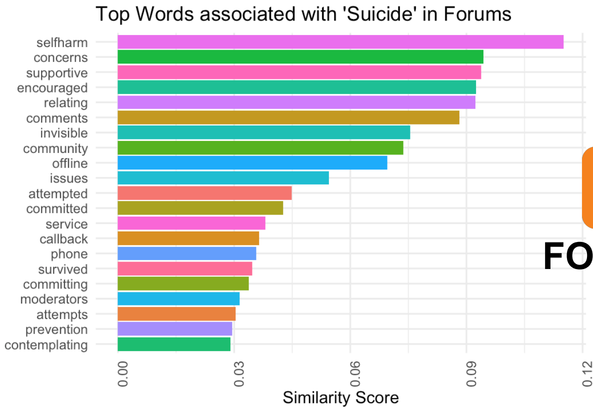


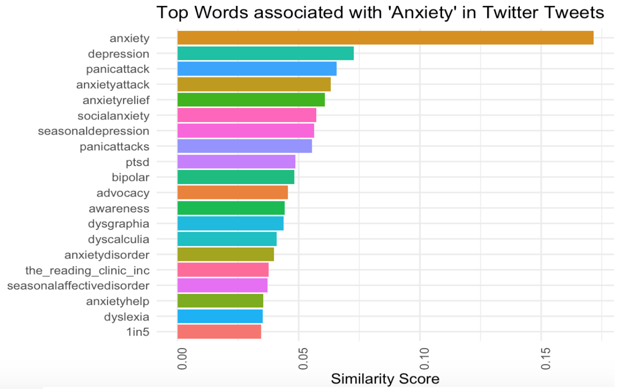
FORUMS

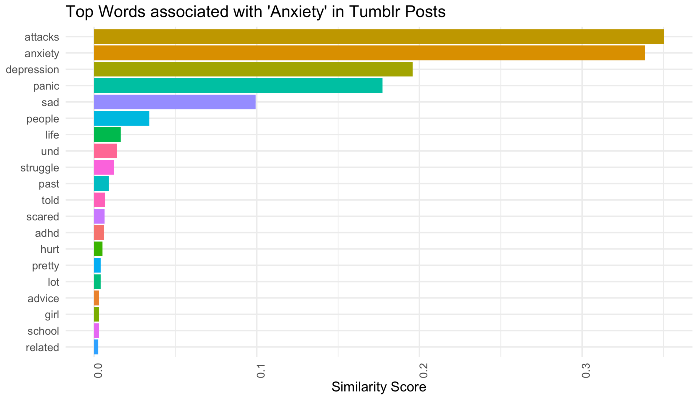


Word2vec

SIMILARITY: ANXIETY

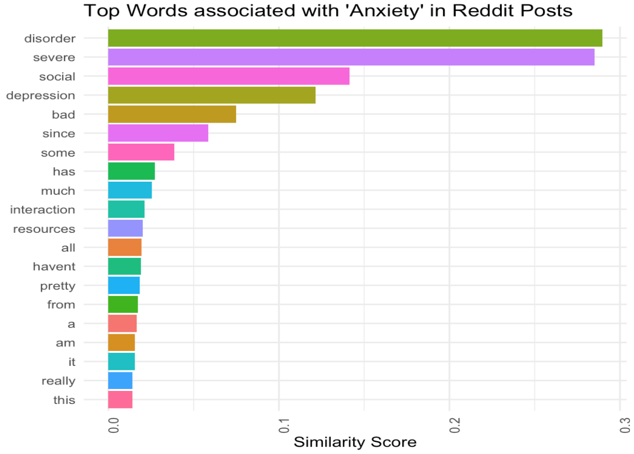
TWITTER

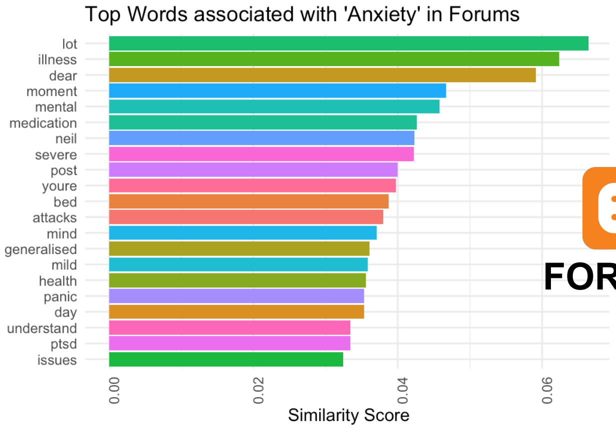




TUMBLR

REDDIT





FORUMS