Identifying social media markers of substance abuse symptoms via tweets: Four predictive models

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Pilot Study
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objective

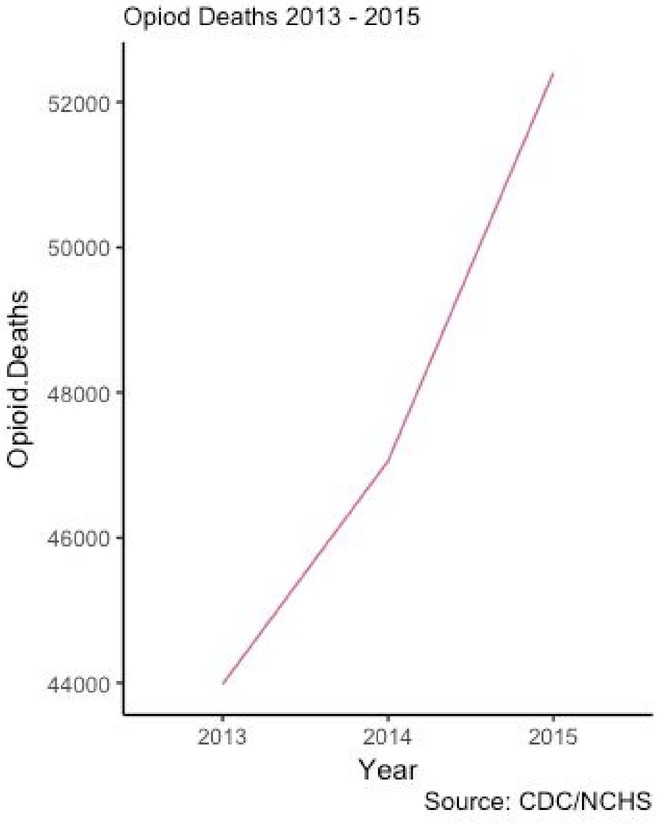
We as clinicians and health data scientists need to assume some responsibility for moving the field in a direction where clinicians are better trained to prevent and recognize drug abuse, especially when working in resource-strapped communities.

Through social media, we can find insight about addiction, recovery, healthcare experience, and more.

This project aims to use computer-human machine learning techniques to identify symptoms and self-reports of heroin substance abuse on social media.

background

Opioid deaths continue to rise in America



Can we identify users as potentially having opioid addiction symptoms based on twitter data?

Note: deaths age-adjusted and population adjusted

- Twitter is one of the most used social media platforms with 300 million monthly users.

- Twitter is a social media interface in which users can microblog by sharing short messages of 280 characters each. Through this interface, users (‘Tweeters’) can report real-time experiences.

- Twitter has been a source for several health-related studies and has been used as a measurement tool for health related quality of life and self-disclosure of symptoms and diagnoses.

DSM-5 opioid use disorder

≥ 2 of following in 12 month period:

- Tolerance
- Withdrawal
- Taking larger amounts for longer periods of time than intended
- Difficulty cutting down
- Craving or strong desire to use
- Time spent drug seeking
- ↓ in social, occupational, or recreational activities
- Recurrent use resulting in failure to fulfill obligations at work, school, or home
- Use in physically hazardous situations
- Continued use despite social or interpersonal problems
- Continued use despite knowledge of persistent physical or psychological problems

are there tweets discussing these very symptoms?

tweets example

search query: “heroin withdrawal”

Again, withdrawal . And again, heroIN .

These patients started to go through withdrawal and dealt with pain. Heroin gets rid of the pain so much better and is far easier to get.

compulsive drinking stopped. No cravings, no withdrawal . I just didn’t need it. My heroin addiction was more complicated, but that was 1990s

Heroin is healthcare, even if only to prevent withdrawal . Quitting heroin can cause problems and ALWAYS has recovery. #HandsOffMyHeroin

Knowing ill never be able to smoke opium or do heroin ever again is so heartbreaking but I never want to go through that withdrawal again.

methods overview

1. search queries based on knowledge of substance abuse terms

   tweets dataset: 208,152 tweets using the following query search terms from the DSM-5 opioid use disorder criteria
2. Collected tweets (tweet text, username, posting time, hashtags, mentions, favorites, and tweet ID) between 2007 and 2017 with GetOldTweets python web scraper code
3. Collected twitter users' profile "user frames" with Twitter API in R includes name, description, statusesCount, followersCount, favoritesCount, friendsCount, url, created, language
4. Narrowed set to one search query: "where can I get heroin" (drug seeking behavior)

   pilot tweets dataset: 1,070 unique tweets
5. Labeled data 1 vs 0 (2 classes)

I annotated the twitter data to avoid noisy data (disingenuous, inappropriate statements, jokes, spam, and quotes)

6. Explored data, feature engineering
7. Split tweets: 75 | 25 split (804
8. Created 4 classifiers built with 75% of the data set and tested 25%. Models were evaluated by applying 10-fold cross-validation.

“yes”, “no”

For each of the 1,070 tweets from the “where can I get heroin” search query, I evaluated the tweets as “yes”, “no”, which resulted in 716 tweets, and 356 tweets, respectively. Tweets appraised as authentic self seeking /self experience labeled 1 (“yes”).

“yes” tweets: 1 (n = 716)
“no” tweets: 0 (n =356)

Examples of “yes” user tweets:

- *@Shaynayynayy haha yeah I figured. Well, on the bright side I know where I can get myself some good heroin now*
- *Where can I get this MS-13 heroin ?*
- *You know where I can get some heroin ? For a friend*

Examples of “no” user tweets:

- *Why did this man just ask me did I know where he can get heroin from ?*
- *America: Where I can buy a scalpel, tarp, zip ties, peroxide & bleach in same order, but try to get needles & OMG NO IT MIGHT BE FOR HEROIN !*

When coding heroin tweets, 0 denoted a tweet that was neither indicative of potential usage for the individual or someone they knew but rather a general statement about heroin, 1 being that the tweet indicated potential heroin usage for the individual.

Tweets coded “1” (seeking heroin personal experience)

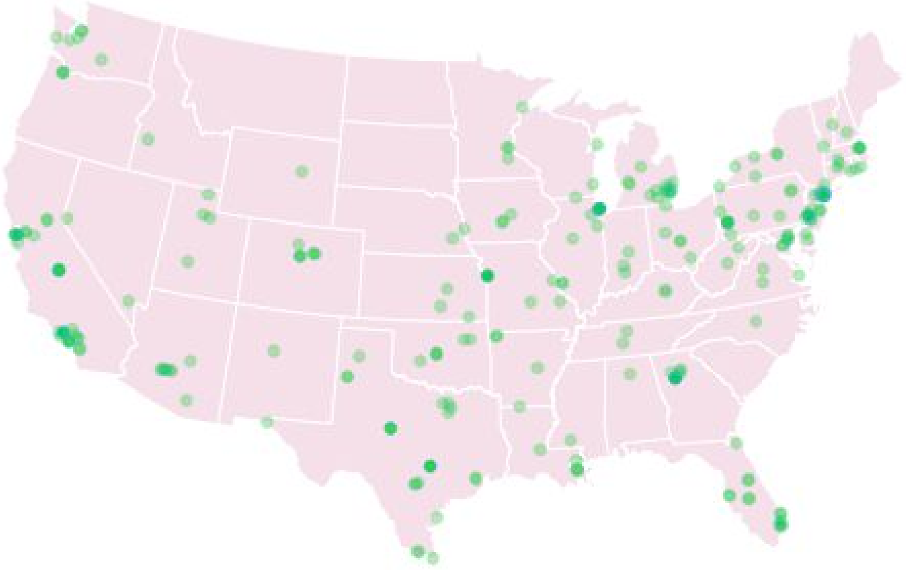
Extracted profile information via Twitter API in R ⟶ Used **Google API** to find coordinates for locations in profile ⟶ Selected for USA

Tweets

Labeled “1”: **716** ⟶

Located in US: **280**

US heroin seeking tweets



Mapped US Heroin Tweets Coded as 1 Seeking Heroin

feature engineering

Created new features based on text in tweet, profile description, username, and name such as:
commas
blanks (spaces)
capital letters
hashtags
mentions
capital letters used first in word
semicolons
numbers used
Sentiment scores of tweets
question marks
length of text
length of username
underscores in username
and more

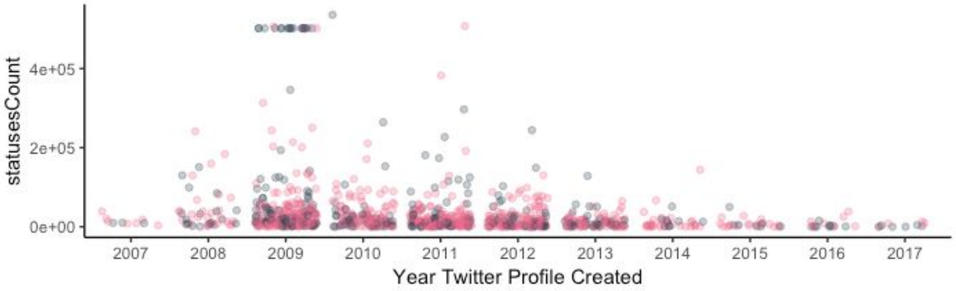
Additionally created new features based on Tweet datetime and profile creation datetime such as:

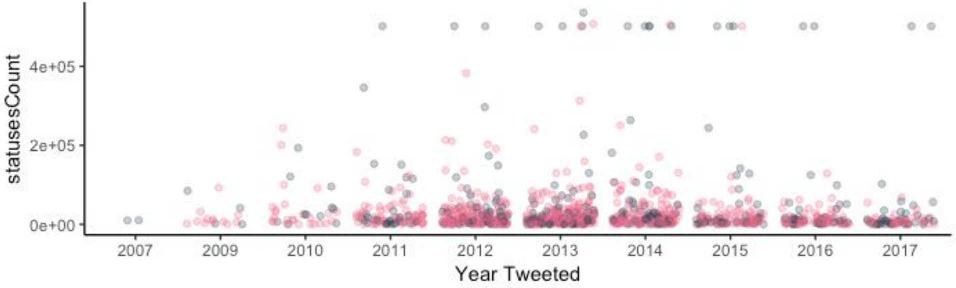
- *hour profile created*
- *hour of tweet*
- *day of tweet*
- *day profile created*
- *whether day was a weekday vs weekend*
- *difference in time between profile creation and tweet*

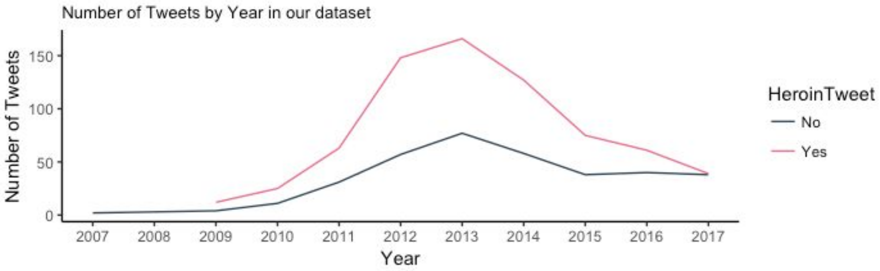
and more

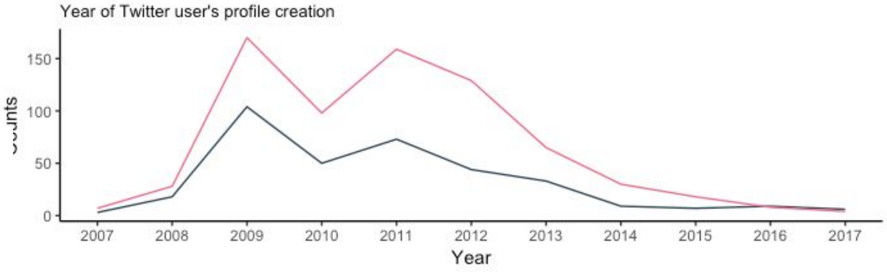
exploratory data analysis

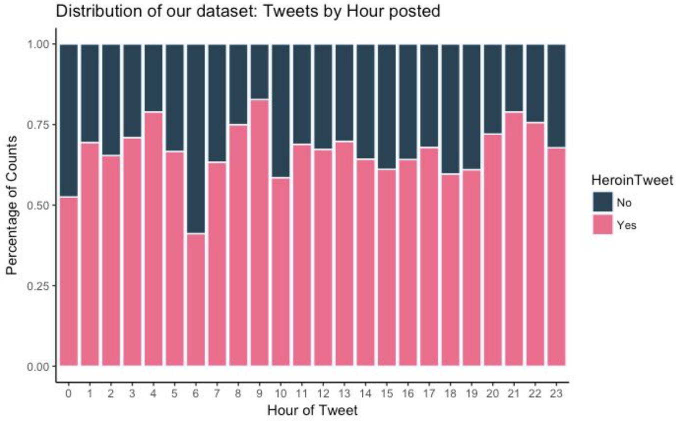
There were cases in Tweets of class “no” (“0”) had many extremely high status counts.
Additionally, tweets made the largest proportion of tweets at posted at 6AM. The proportion of tweets at all other hours were largest in Class “yes”.



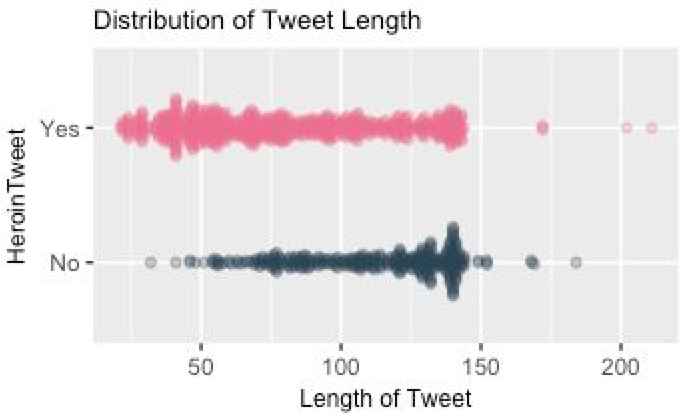


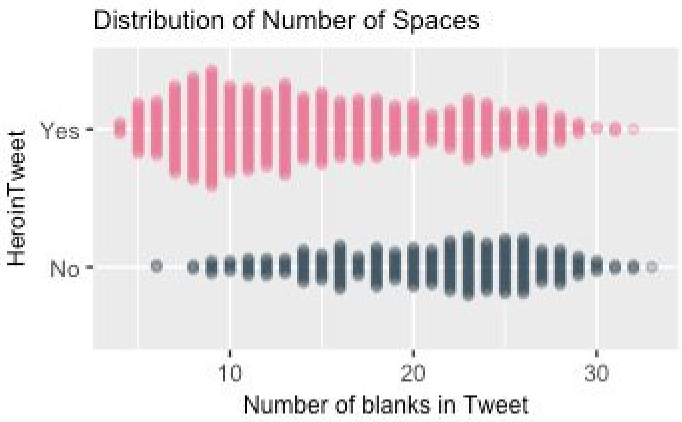


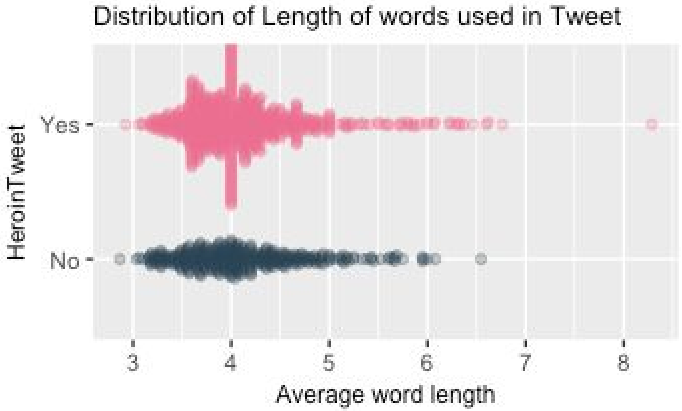


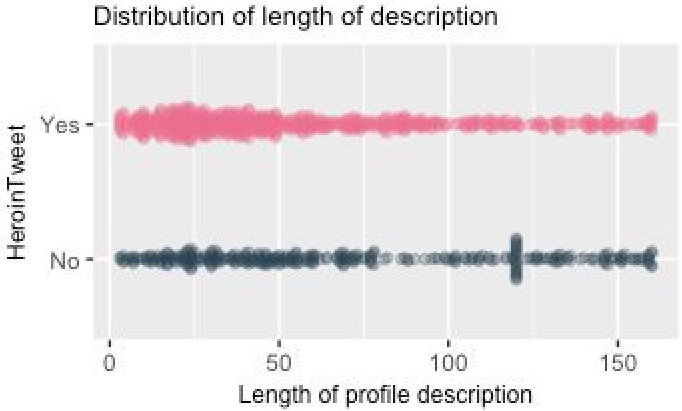


exploratory data analysis



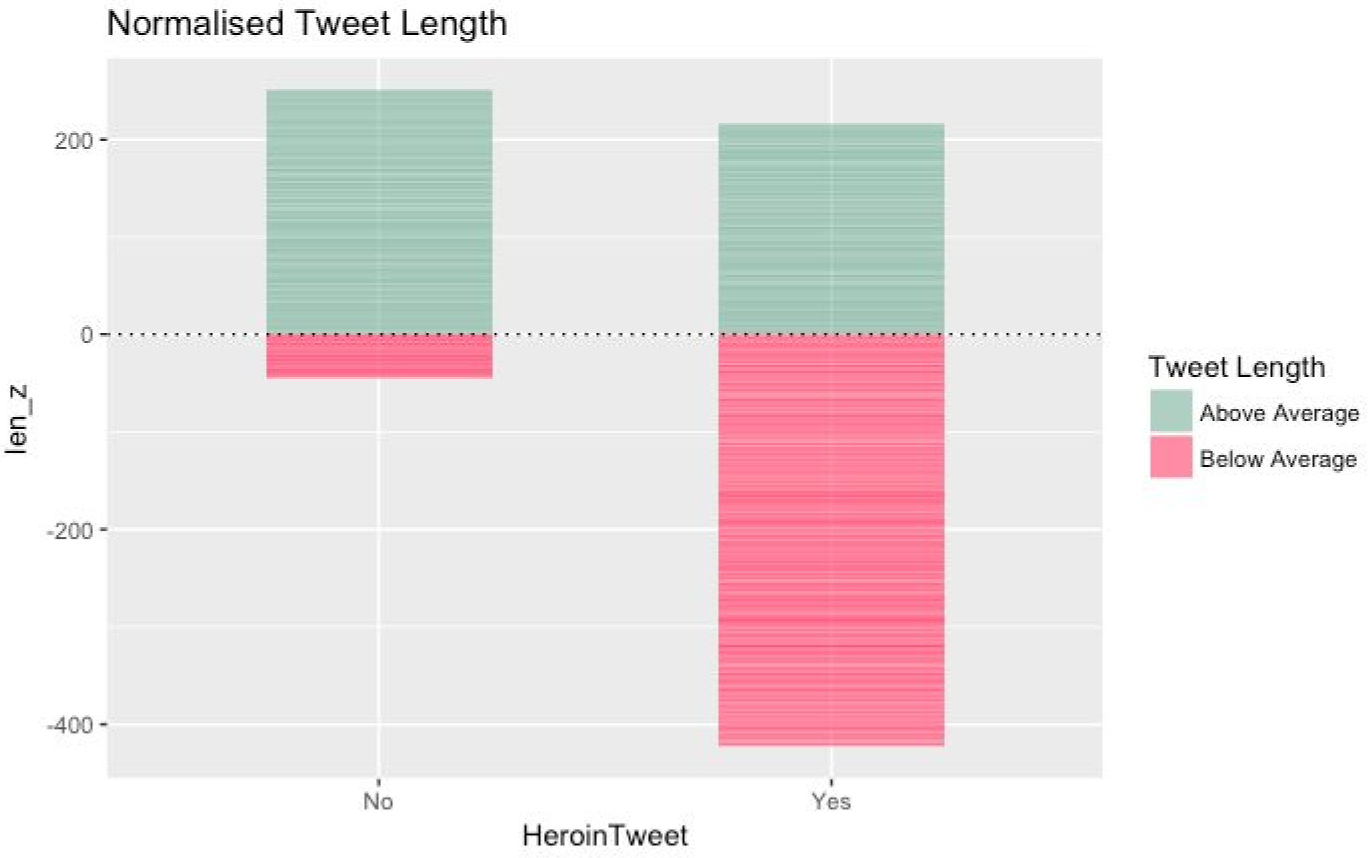






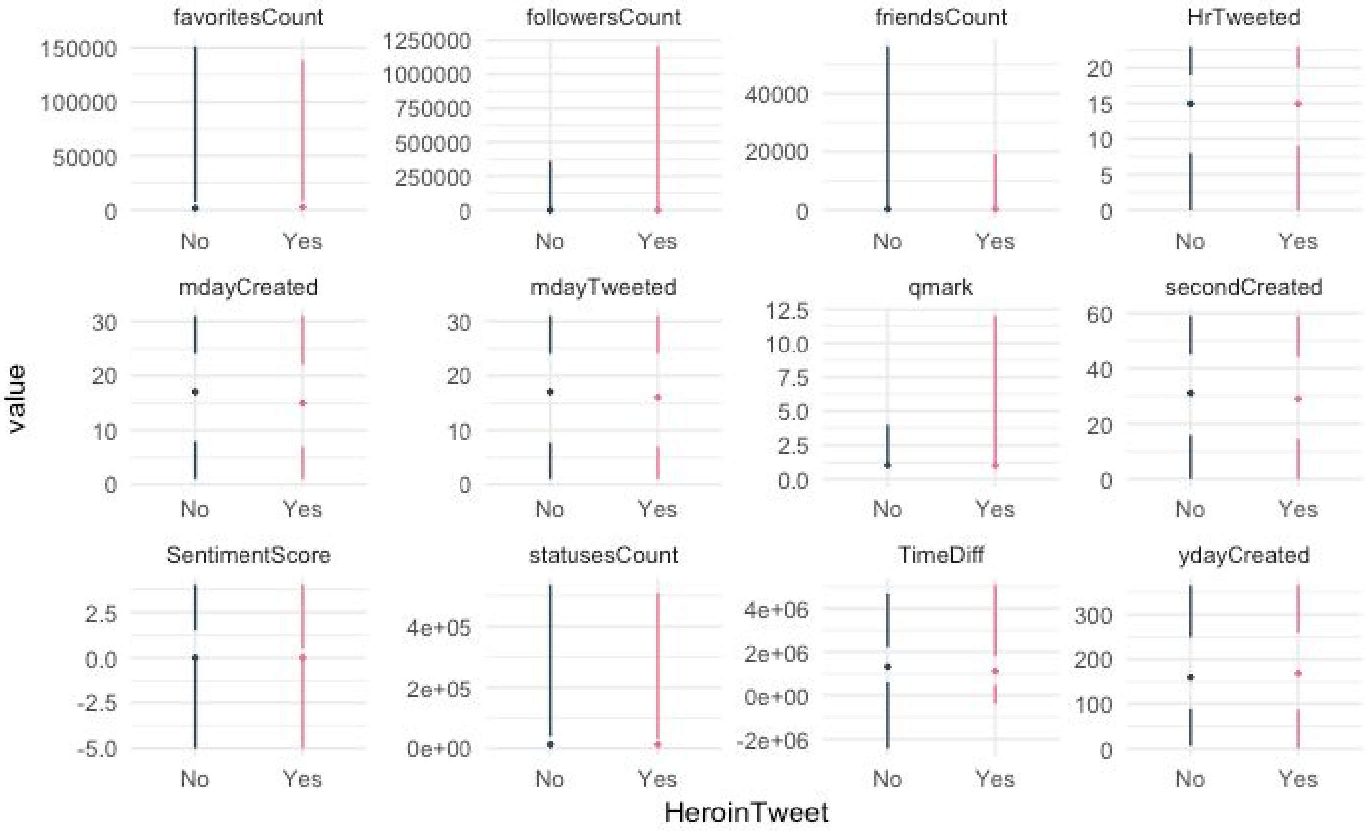
Differences can be seen among the distribution of various features between Heroin Tweets in class “Yes” vs class “No”.

feature engineering: tweet length

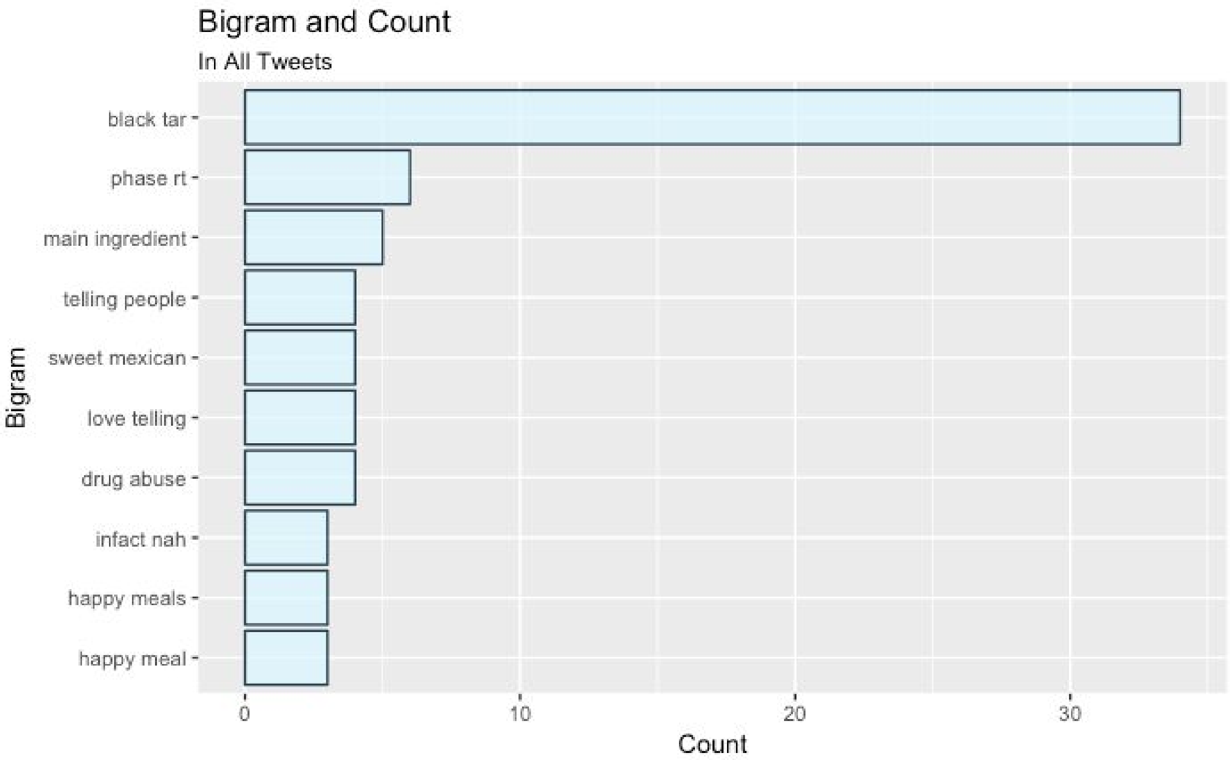


exploratory data analysis

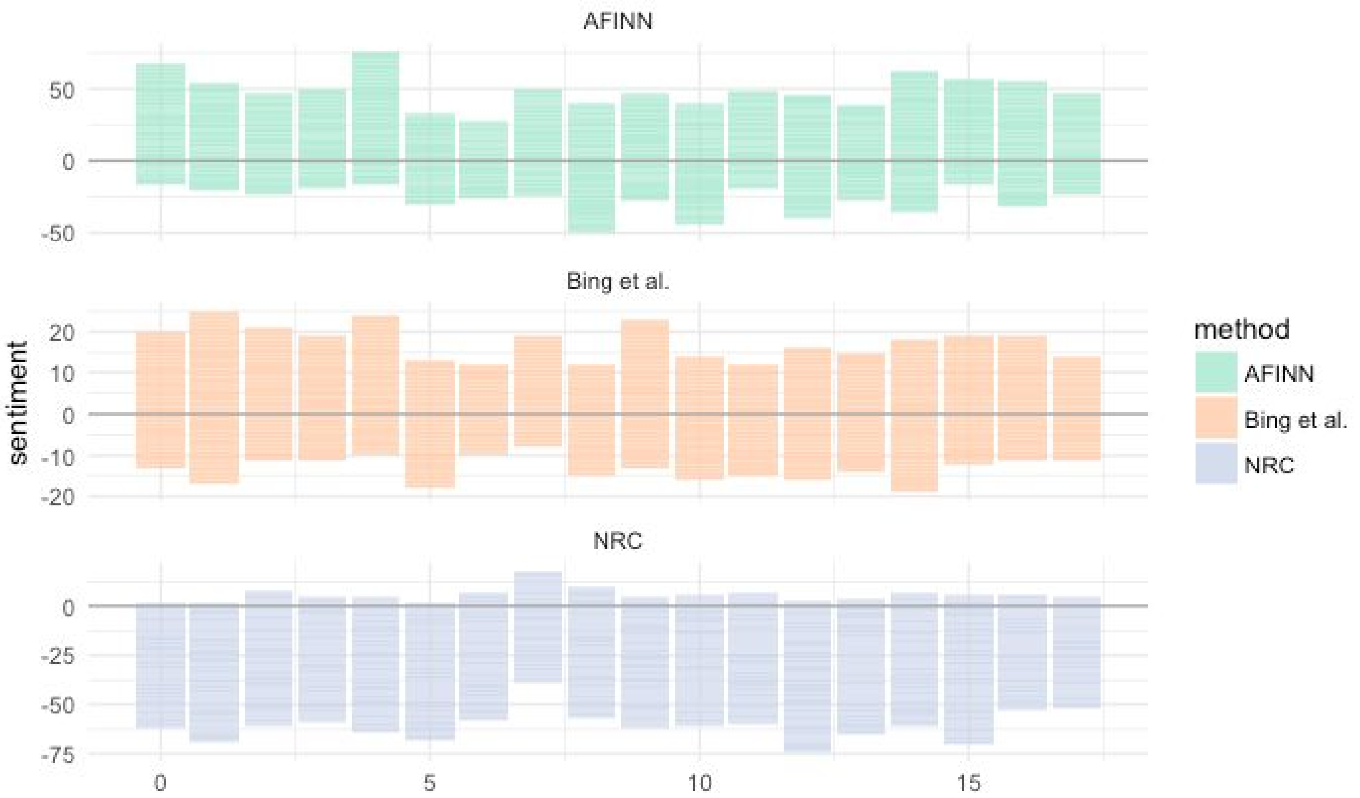
Some distributions of variables did not appear to have much difference between Tweet Classes.



Natural Language Processing



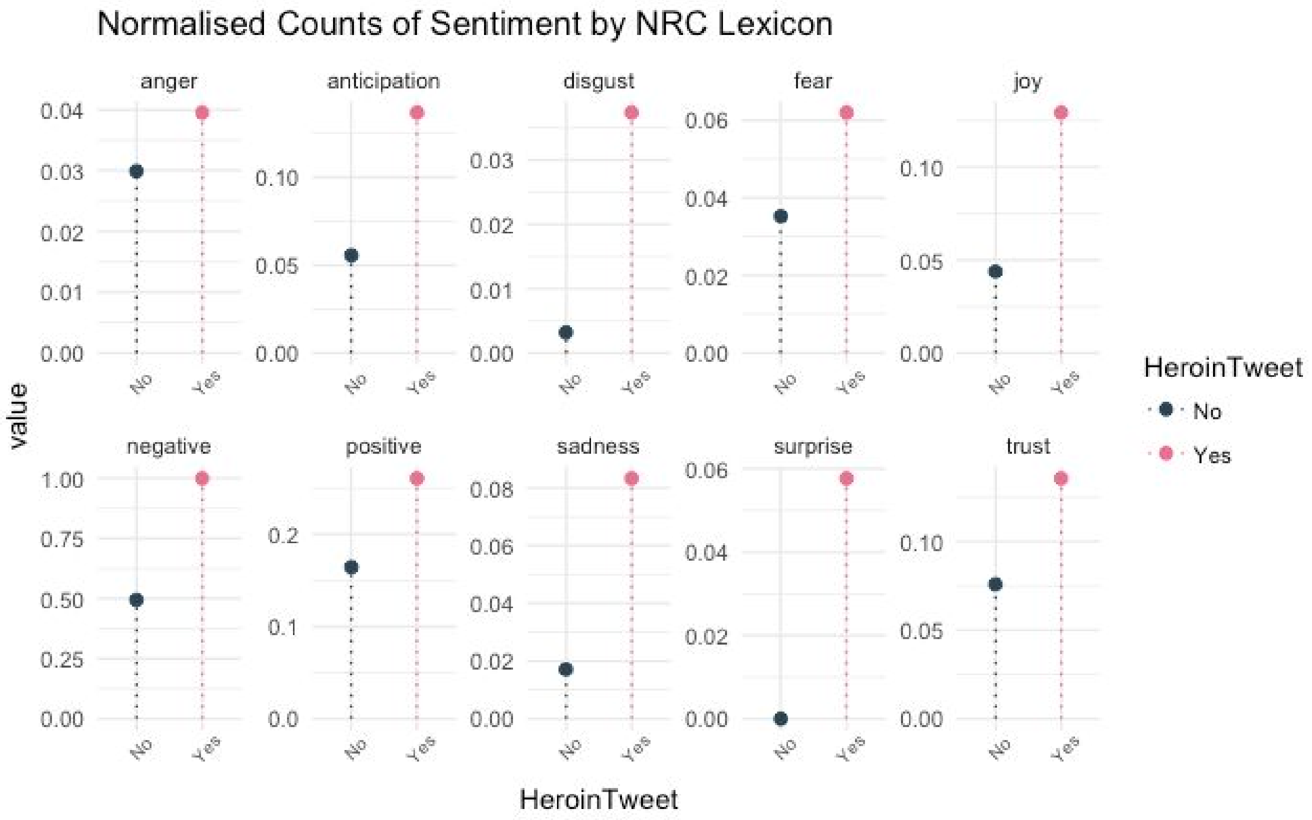
NLP feature engineering: Sentiment Analysis



Counts of emotion words from NRC of each tweet was used in the models.
As well as average sentiment scores for each tweet using the AFINN Lexicon.

NLP feature engineering

Counts were added from the NRC Lexicon for “anger”, “anticipation”, “disgust”, “fear”, “joy”, “negative”, “positive”, “sadness”, “surprise”, “trust”. The counts of negative words in each tweet was an important feature in the XGBoost model.



feature engineering: SentimentScore

- ultimately chose to use AFINN lexicon for this feature
- mean sentiment score for words grouped by unique tweet id
- sentiment scores ranged from -5 to +4

Highest scoring sentiment tweets

2016-08-20 18:22:00
"He says to my Tia "Maggie, where can I get some heroin , the weed isn't getting me high anymore" lmao"

2012-08-08 12:18:00
Well ik where I can get coke....lmao but i 'd never do coke or heroin ! #toohardcore

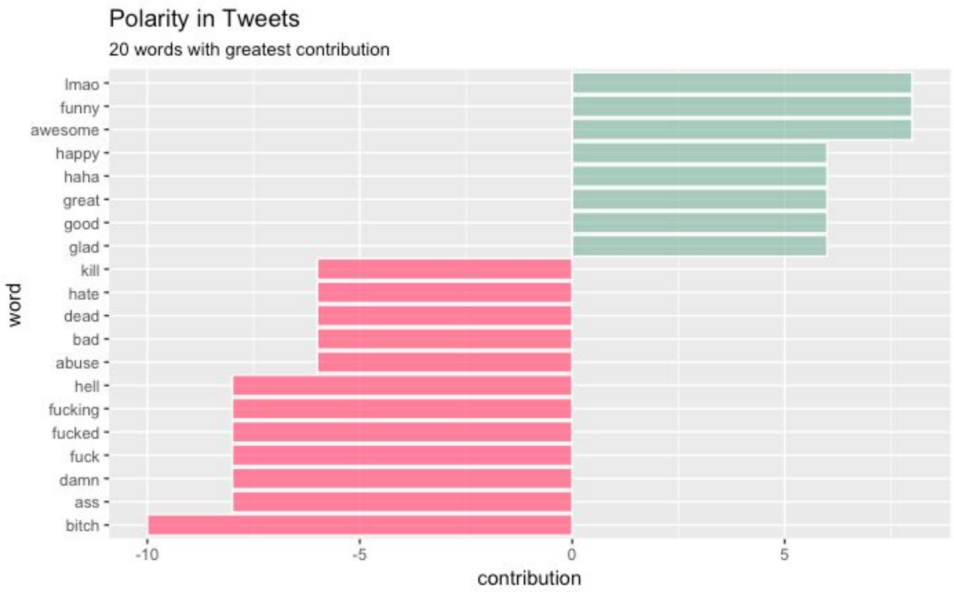
2010-09-29 08:50:00
@BrightonArgusJo I know a corner where you can get some absolutely wonderful organic heroin . #HoveGhetto

Lowest scoring sentiment tweets

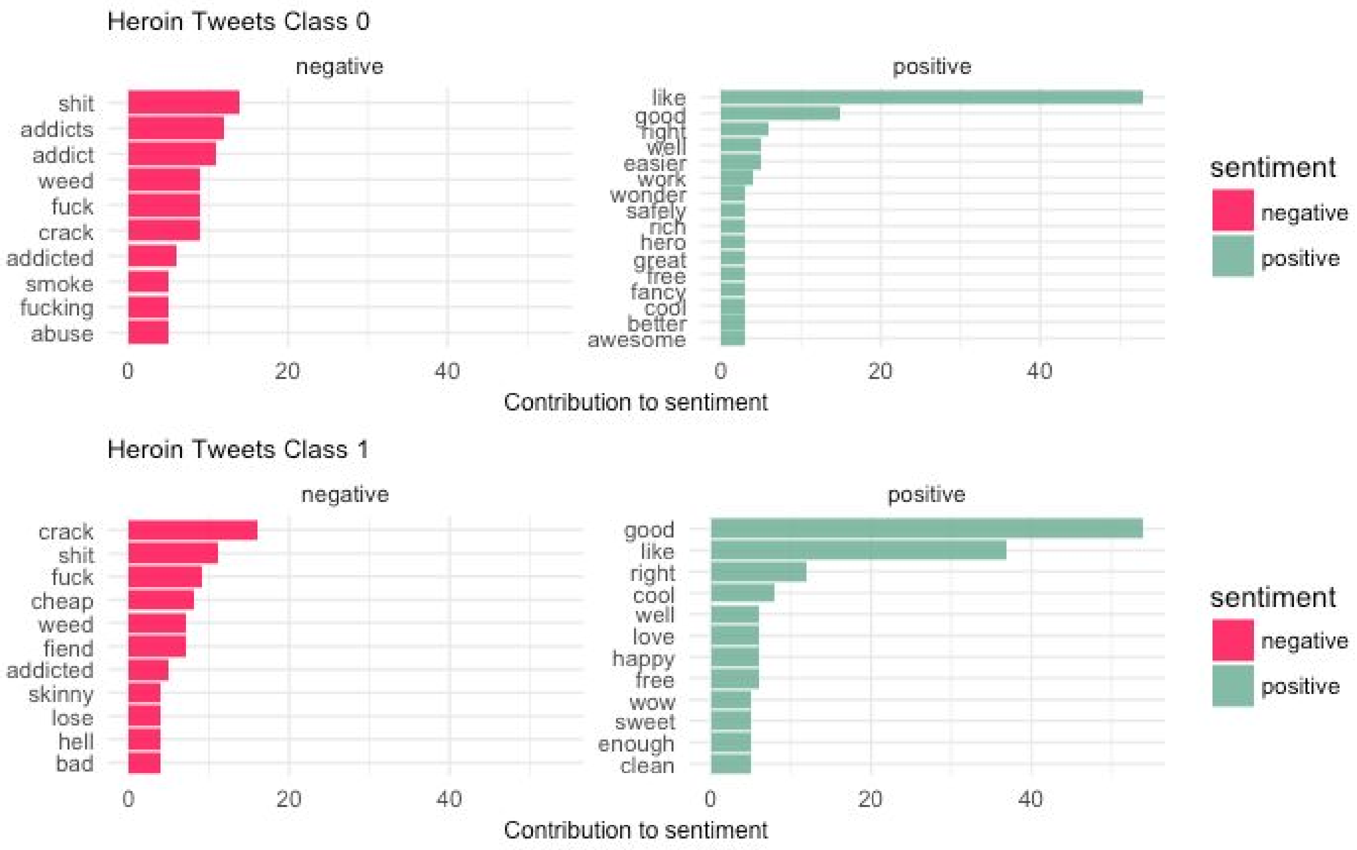
2014-12-14 17:56:00
Fuck off you heroin slut. Don't ask me where I can get some detox pills for you. Send your ass to rehab. Not ask where to get some.

2014-11-20 01:27:00
I live in a place where a guy can get the shit beat out of by a deer and a heroin bitch can go to jail and My friends will just relish it.

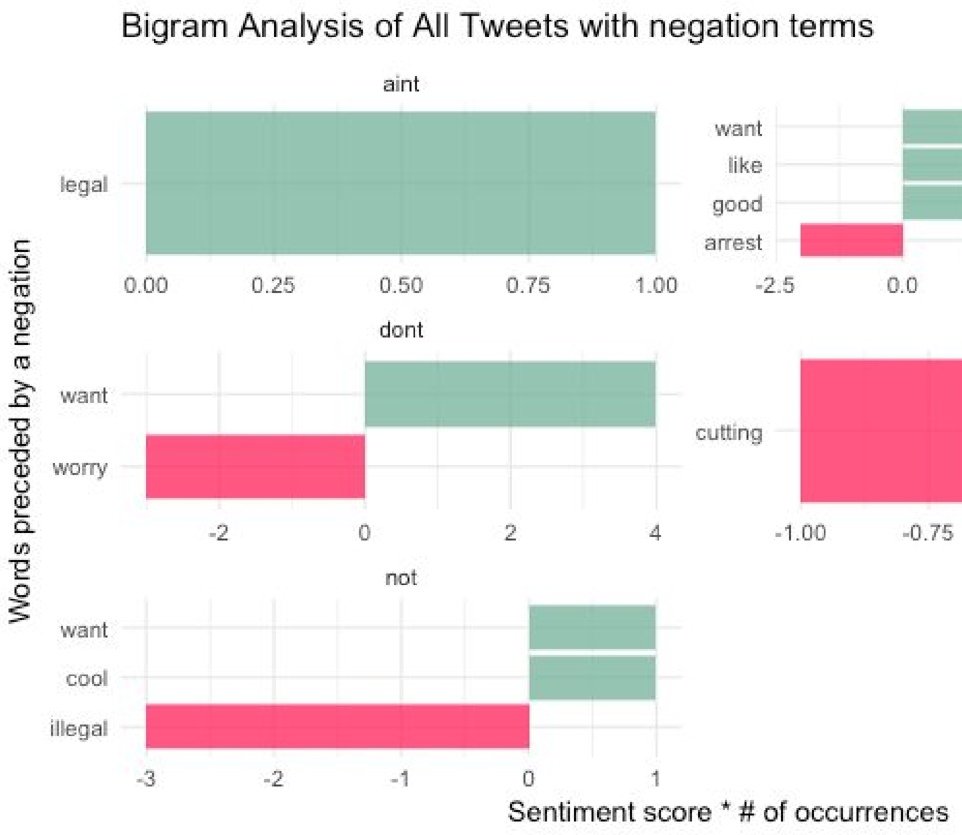
2014-05-21 11:41:00
Anybody know where I can get some heroin on the cheep so my parents have a reason to bitch other than me chewing..



feature engineering - sentiment using “bing” Lexicon

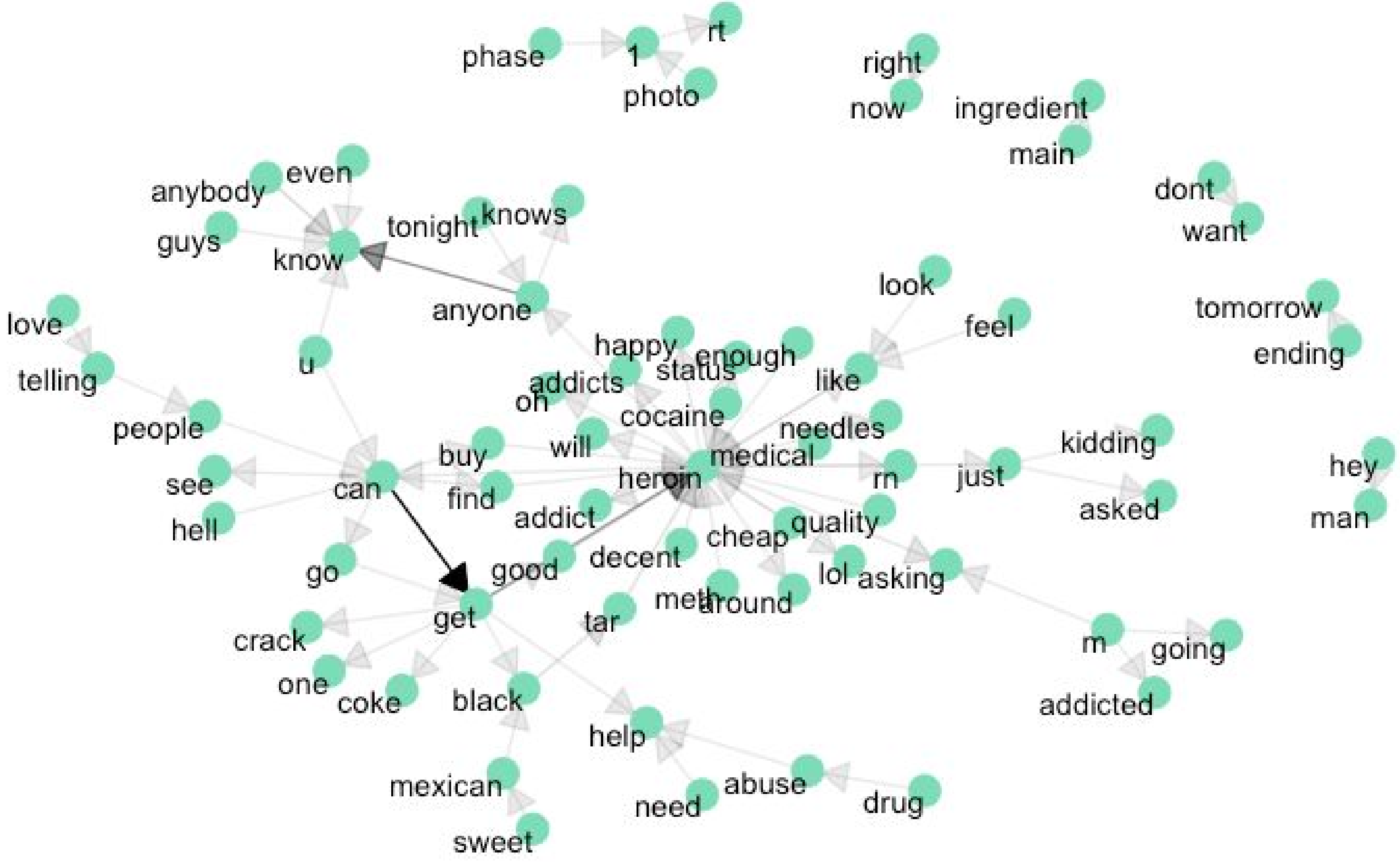


bigram analysis

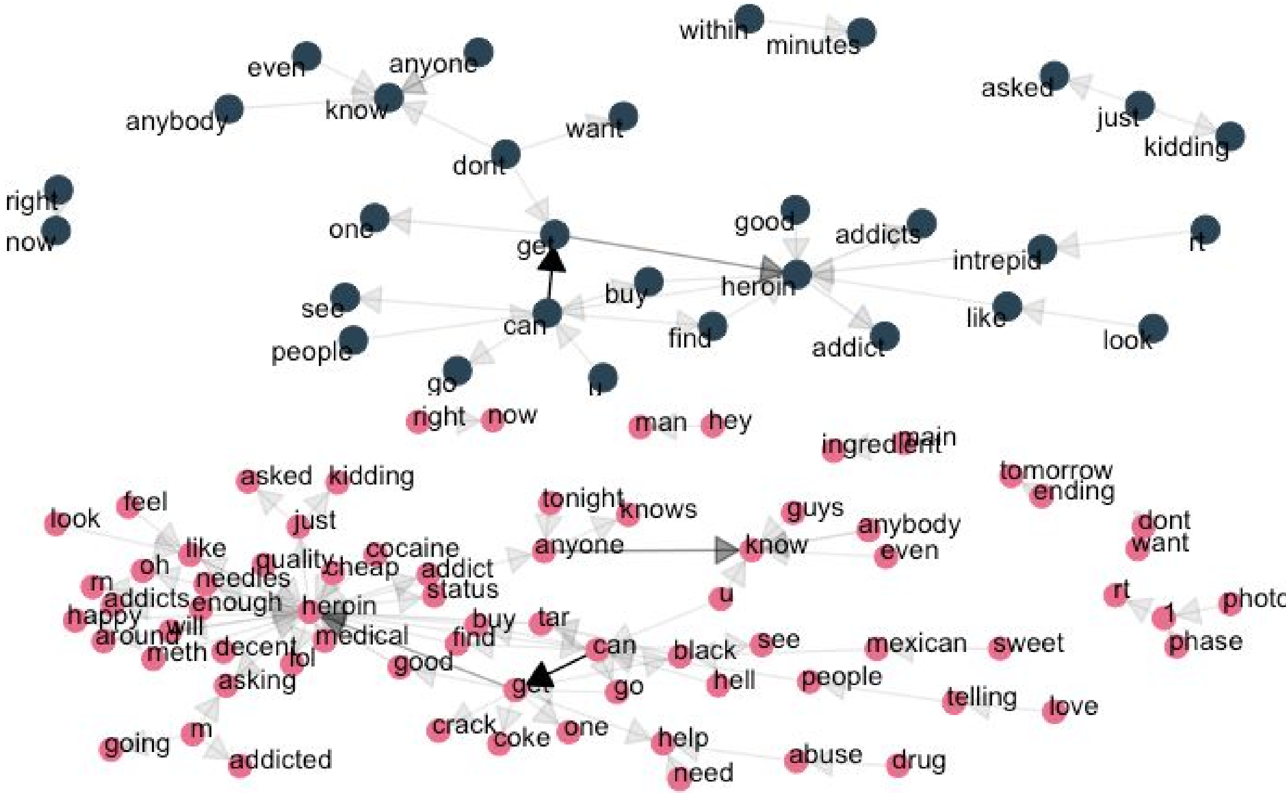


negation terms before: sentiment determined with "AFINN" Lexicon

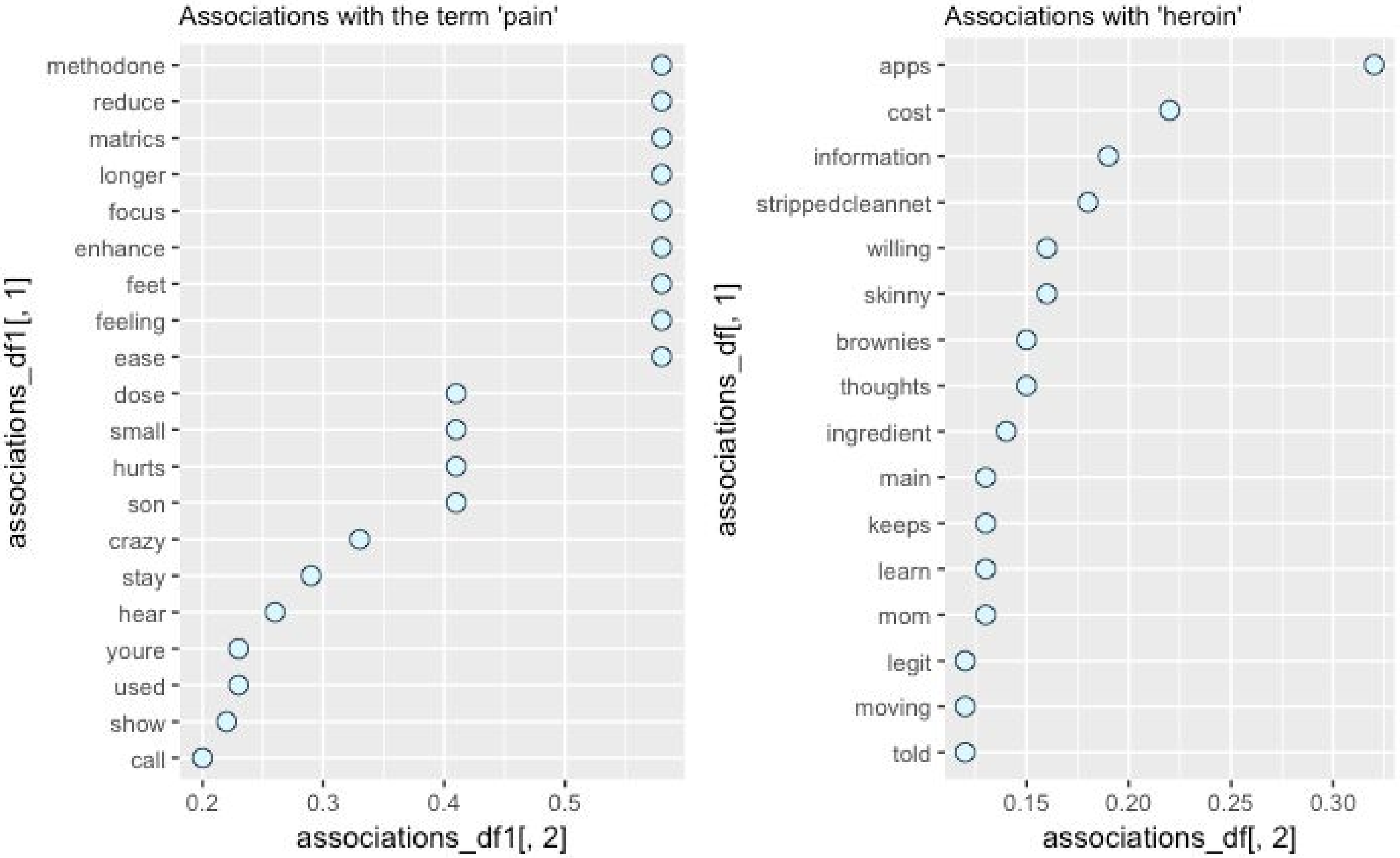
bigram analysis - all 1,070 tweets (1 and 0)



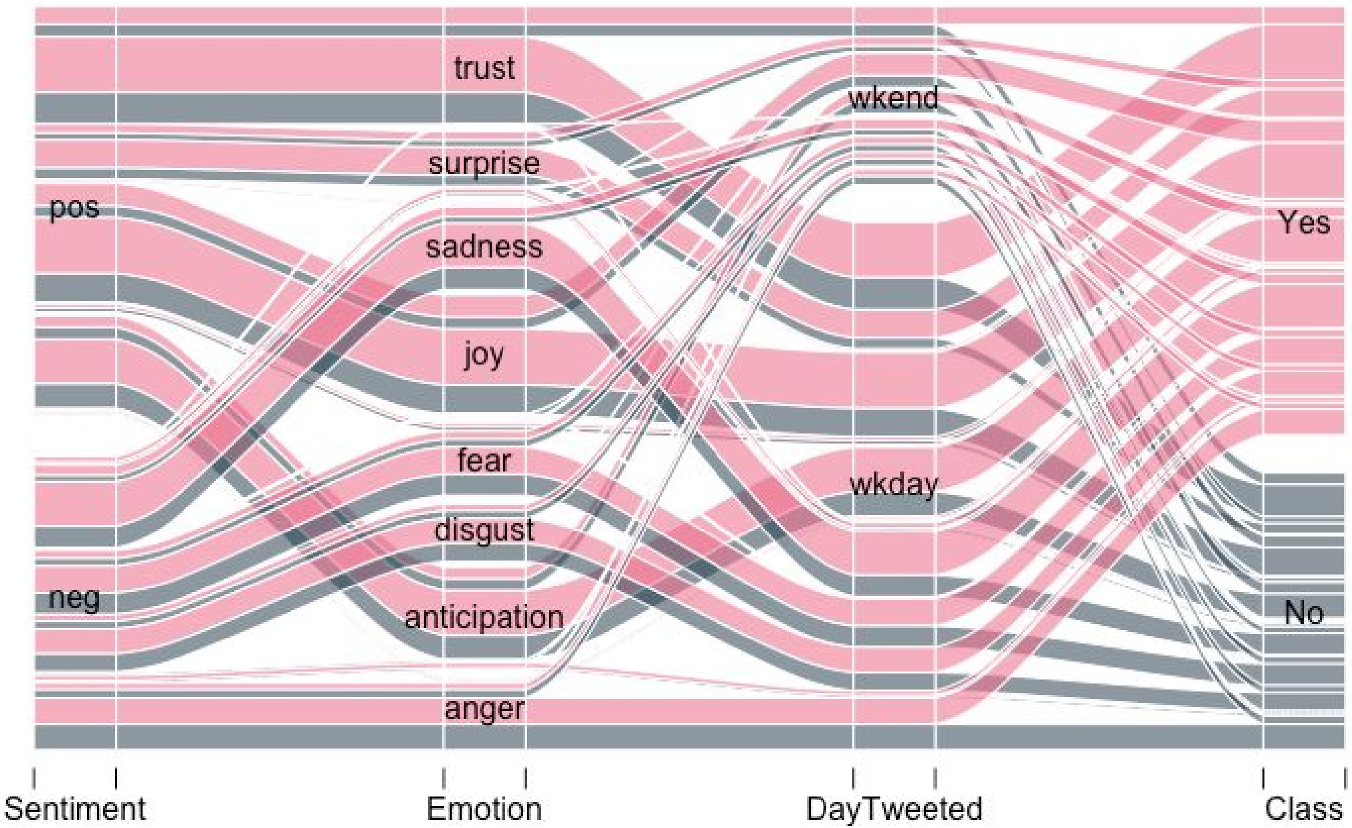
NLP and bigram analysis - yes vs no tweets



bigram analysis - associations

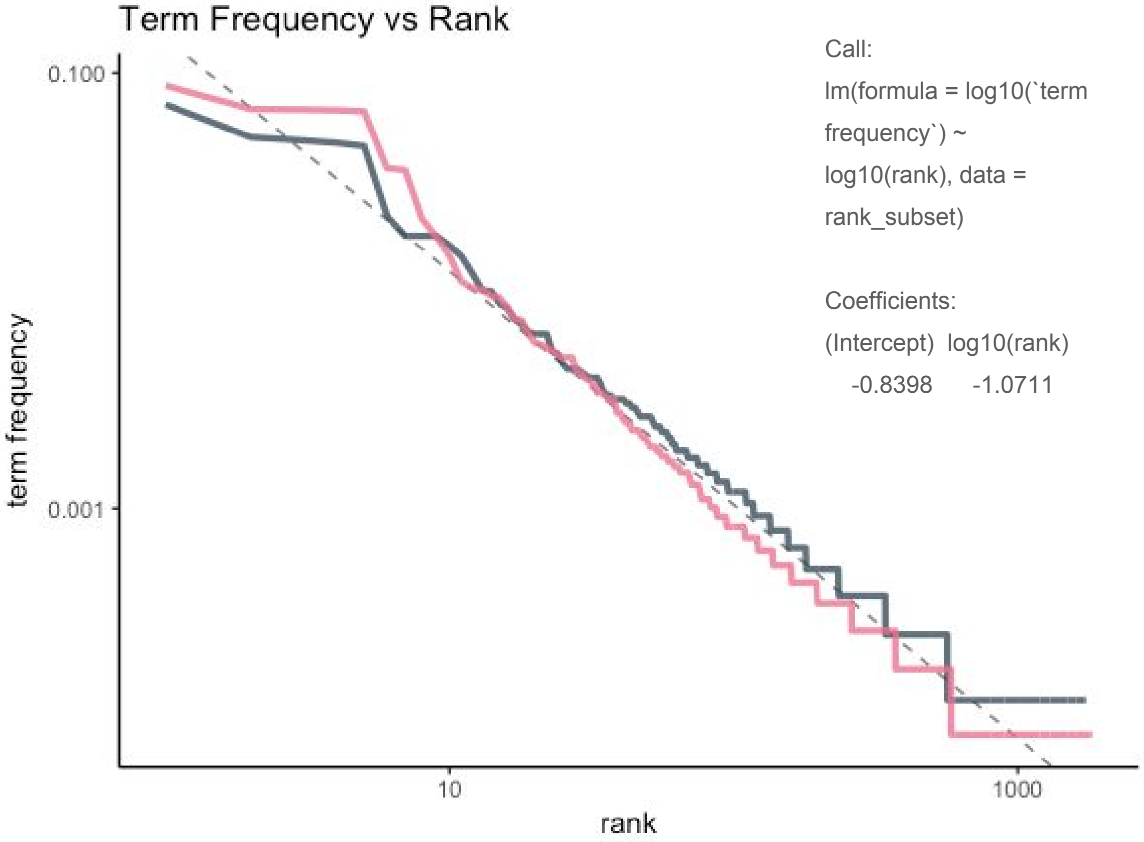


feature engineering continued



Zip’s Law

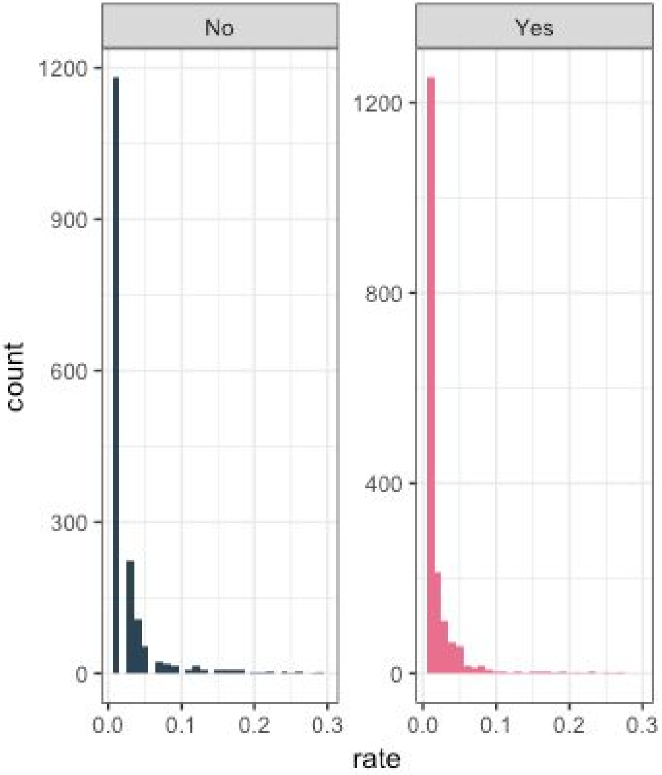
deviations are seen at both high rank and low rank, which is usually unusual



Call:
lm(formula = log10(`term frequency`) ~ log10(rank), data = rank_subset)

Coefficients:

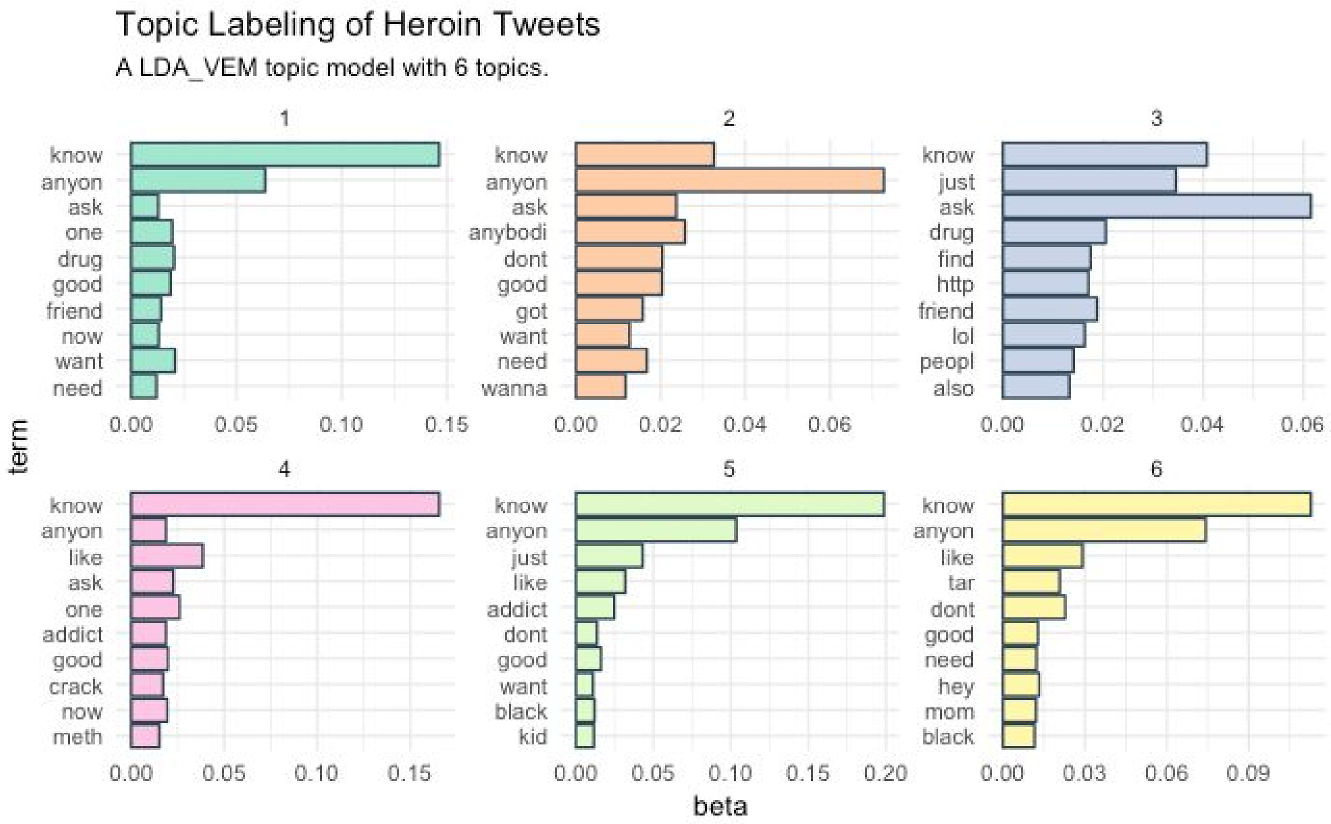
(Intercept)	log10(rank)
-0.8398	-1.0711



NLP:

Latent
Dirichlet
allocation
(LDA)
Topic Modeling

LDA topic modeling mirrors natural language in that terms overlap and seeks to explain how the words in the documents are related.



NLP: TF-IDF

term frequency–inverse document frequency

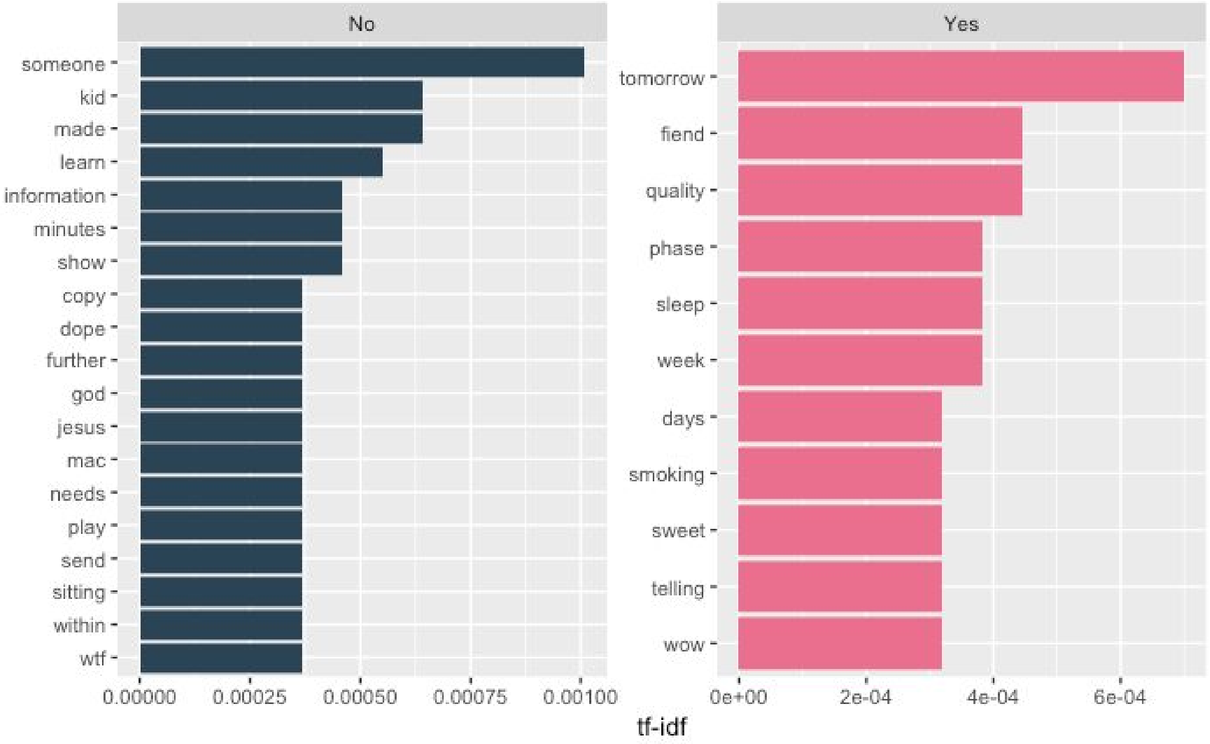
TF(*t*) = (Number of times term *t* appears in a document) / (Total number of terms in the document)

IDF(*t*) = log_e(Total number of documents / Number of documents with term *t* in it).

Value = TF * IDF

Features were made from the DocumentTermMatrix of the tweet text, removing sparse terms within 0.998, and weighting given to TF-IDF.

Result: *456 features*



machine learning

- no n-grams
- only “tokens” or “words” with topic labeling
  - *456 features from tweet text*

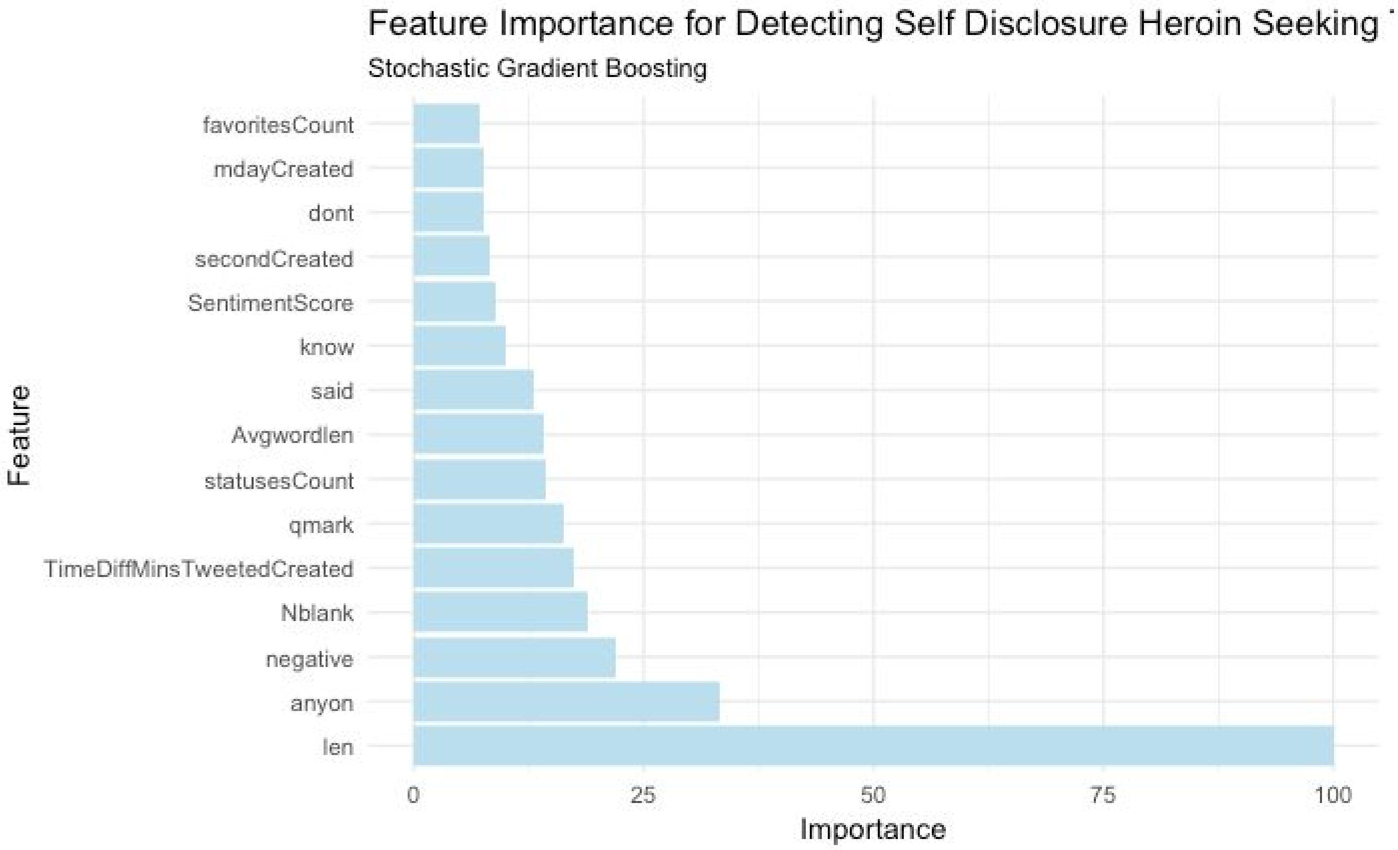
- final features from tweets + userFrame info: *542 features used in total*

75 | 25 random split

train set = *804* observations

test set = *268* observations

model1: SGB



Stochastic Gradient Boosting

804 samples

542 predictors

2 classes: 'no', 'yes'

No pre-processing

Resampling:

Cross-Validated (10 fold)

final model:

n.trees = 100

interaction.depth = 2

statistics:

max ROC: 0.8239

max sensitivity: 0.5812

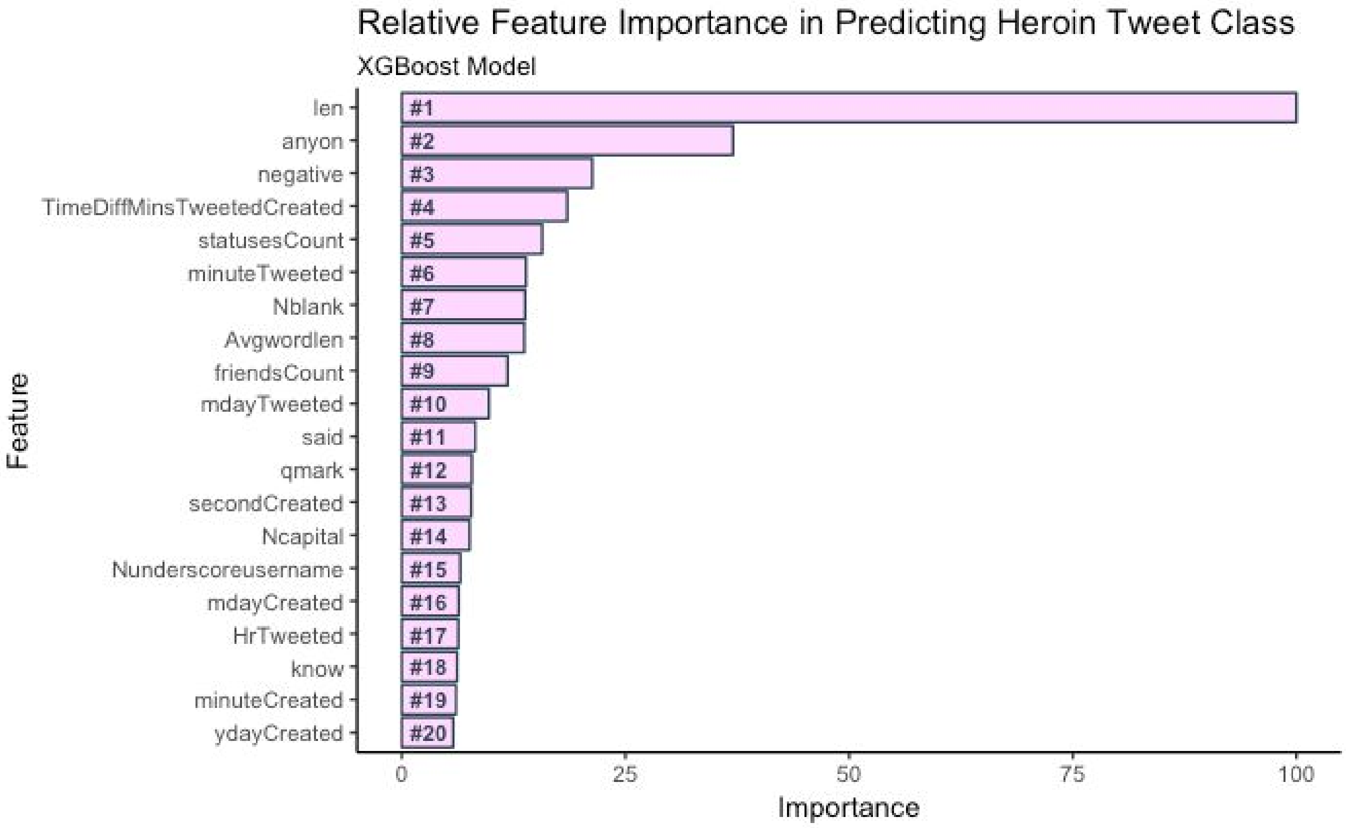
max specificity: 0.8945

predictions:

Area under the curve:

0.7922

model2: XGB



eXtreme Gradient Boosting

804 samples

542 predictors

2 classes: 'no', 'yes'

No pre-processing

Resampling: Cross-Validated (10 fold)

Resampling results:

logLoss: 0.5328789

Tuning parameter

‘nrounds' held constant at 500

‘max_depth' held constant at 3

eta' held constant at 0.05

'gamma' held constant at a value of 0

'colsample_bytree' held constant at 0.8

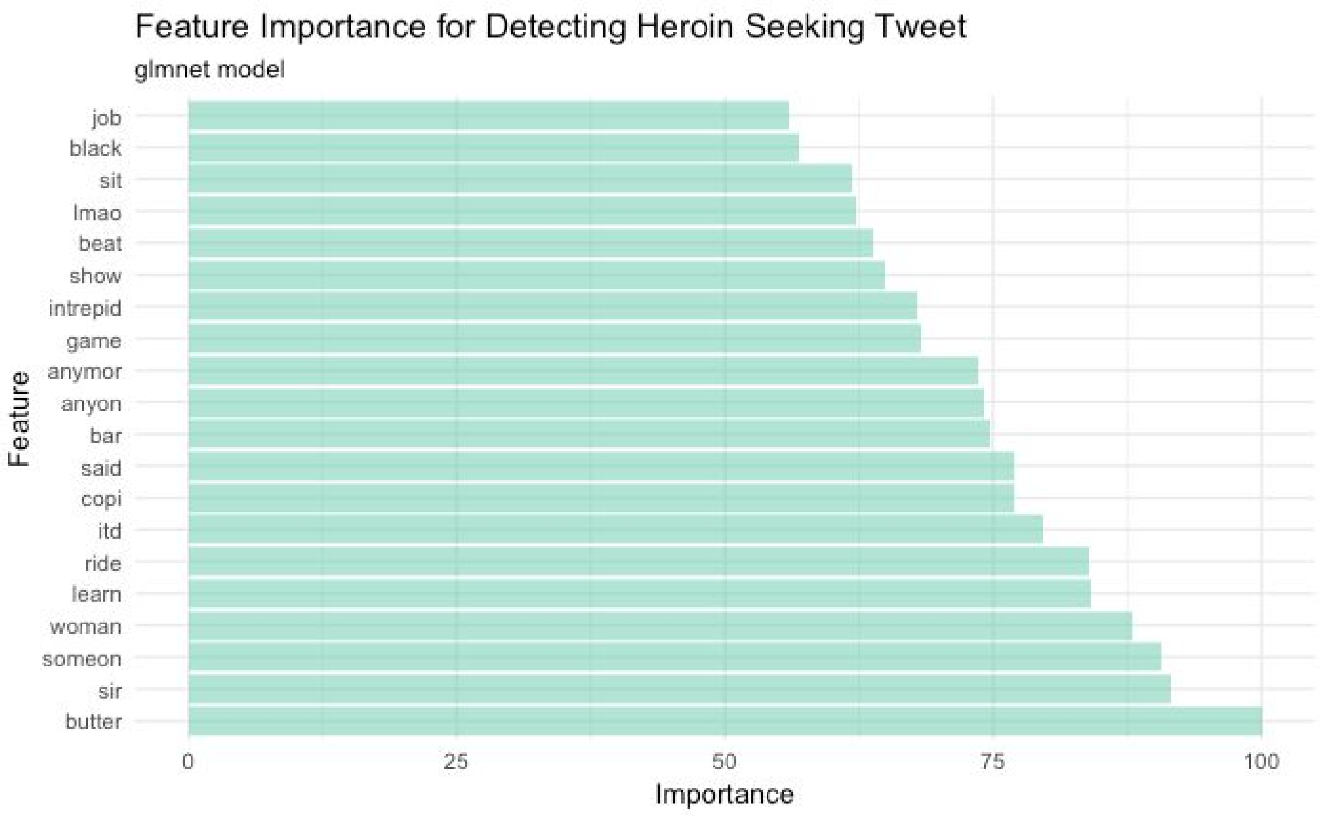
‘'min_child_weight' held constant at 1

'subsample' held constant at 1

predictions:

Area under the curve: 0.8029

model3: glmnet



glmnet

804 samples

542 predictors

2 classes: 'no', 'yes'

No pre-processing

Resampling:

Cross-Validated (10 fold)

final model:

logLoss was used to

select the optimal model

using the smallest value.

alpha = 0.55

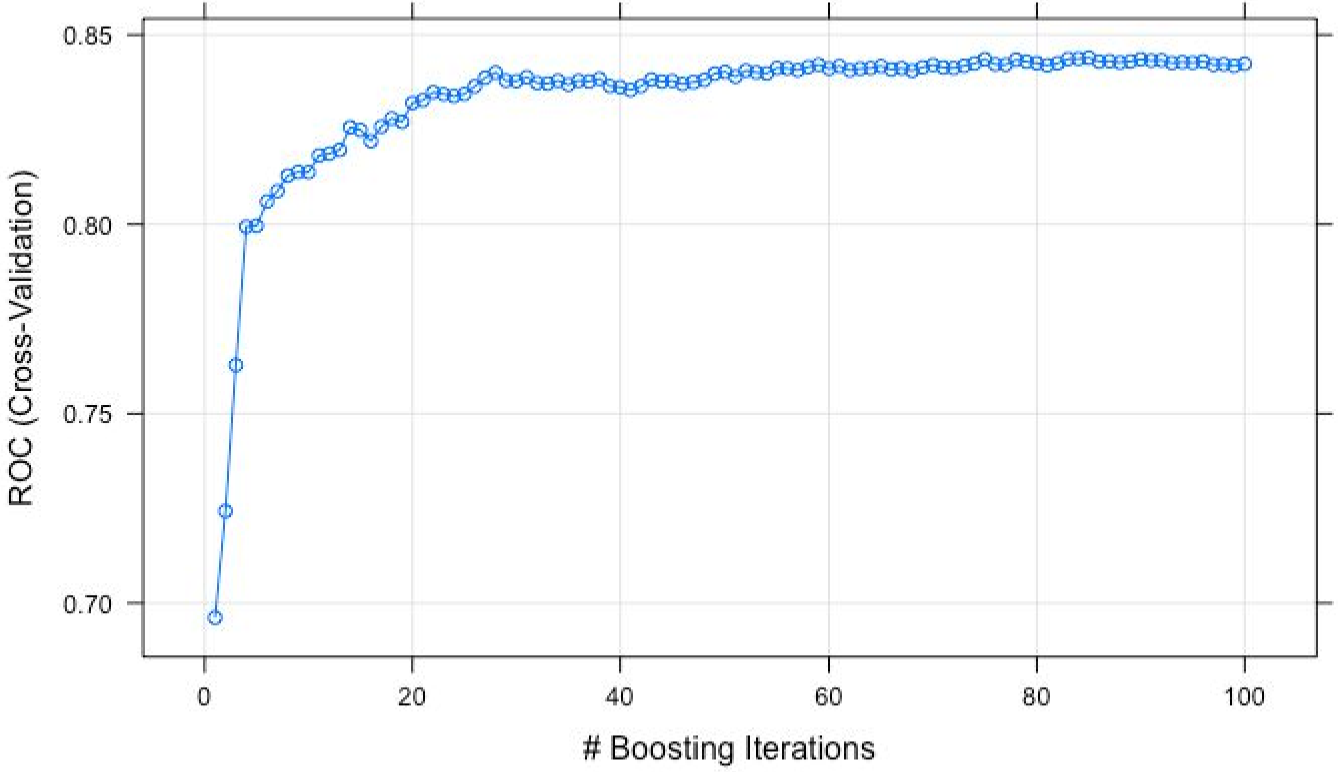
lambda = 0.03815.

predictions:

Area under the curve:

0.8178

model4: c50



C5.0

804 samples

542 predictors

2 classes: 'no', 'yes'

No pre-processing

Resampling:

Cross-Validated (10 fold)

final model:

trials = 85, model = tree

and winnow = FALSE.

statistics:

max ROC: 0.8440

max sensitivity: 0.5925

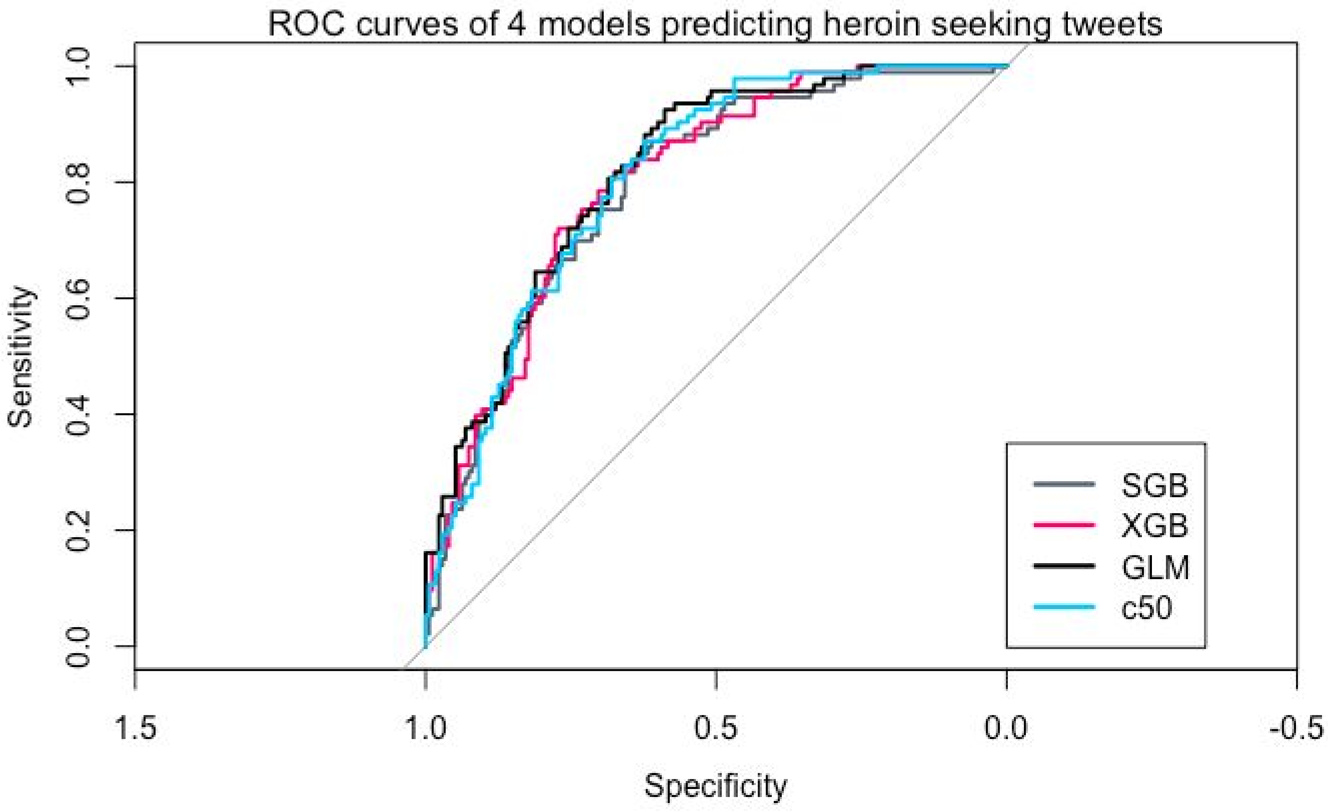
max specificity: 0.8688

predictions:

Area under the curve:

0.8073

machine learning: performance



AUC:

SGB < XGB < C50 < GLM

AUC	model
0.7922	SGB
0.8029	XGB
0.8073	C5.0
0.8178	GLMNET

results: glm

Actual	Predicted	newclass
0	0	TN
0	1	FP
1	0	FN
1	1	TP

GLM	newclass
42	TN
51	FP
23	FN
152	TP

The models, glmnet, had the highest AUC on the test set.

Exploring those results using the raw predictions and creating a confusion matrix:

FN	FP	TN	TP
23	51	42	152

The model performed relatively poorly with *accuracy* only at 0.7349, *classification error rate* at 0.2761, and *precision rate* at 0.7488.

The model had a *true positive rate*, or sensitivity, of 0.8686, *true negative rate*, or specificity of 0.4516, an *F1 score* of 0.8042, and an *AUC* of 0.8178

Metric	Value
Accuracy TP + TN /(TP + FP + TN + FN)	0.7349
Class Error Rate FP + FN /(TP + FP + TN + FN)	0.2761
Precision TP /(TP + FP)	0.7488
Sensitivity TP /(TP + FN)	0.8686
Specificity TN /(FP + TN)	0.4516
F1 Score 2(Precision * Sensitivity) / (Precision + Sensitivity)	0.8042
AUC	0.8178

conclusion

Differences were identified in the heroin seeking texts and twitter information. For example, among heroin seeking texts, absolute value of sentiment scores were higher, tweet length was more variable, normalised tweet length was shorter, and negative words appeared more. Stem words: “anyon” and tokens in phrases such as “black tar”, a street name for heroin, were shown to be important in identifying heroin seeking texts from non heroin seeking texts

The outcomes of this project indicate that we must continue to use social media to find novel ways to engage and connect services with drug users online. These may be crucial to overcome some of addiction’s biggest challenges by using digital technology.

further hopes & future plans

- Substance abuse addiction is a disease that already faces much stigma
- Hope that by using machine learning techniques to identify authenticity of Tweeters' heroin and opioid abuse, we can link them to resources such as methadone clinics and needle exchanges.

FUTURE

Future plans include incorporating more feature engineering, such as to capture emoji sentiment, profanity, abbreviations, and LIWC to get personality attributes.

Additionally, have an expert or second person validate my classifications.

Questions?

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