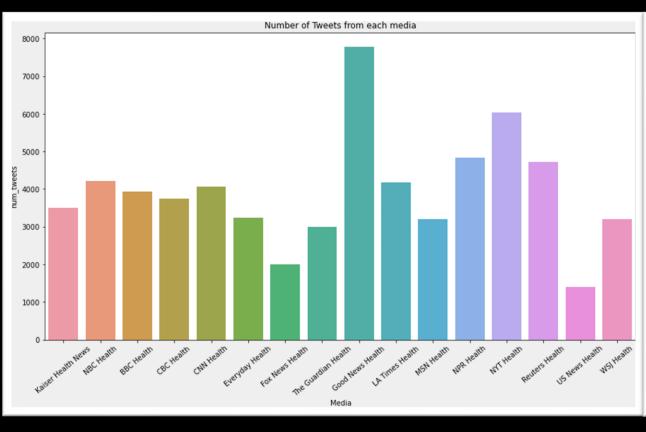
DTSA 5510 Unsupervised Learning Final Project Health News Tweets Categorization

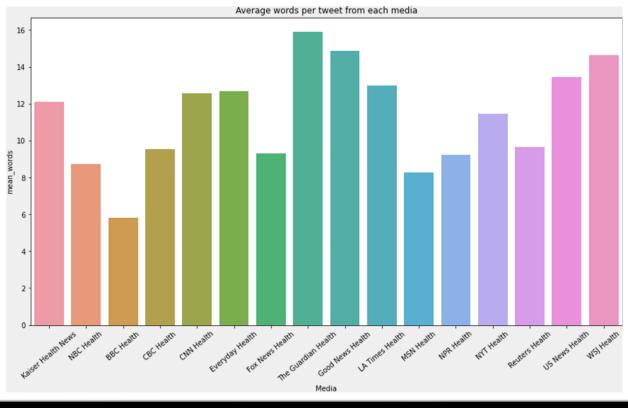
### Data and Problem

- We saw word vector based model worked well with news articles in module 4
- What if each document is much smaller, specifically Twitter text?
- Can we predict the attributions of tweets or the accounts from texts alone?
- Can we find meaningful latent factors from texts?
- The data was downloaded from UCI Machine Learning Repository
- The data contains 63K tweets from 16 health news accounts
- o I will use 1,200 tweets from each media, except for the TFIDF analysis

## Data Distribution

Number of tweets and average words per tweet





# TF/IDF 1-2 ngrams

10 words with the highest TFIDF scores from each news source

Many of them confirm our perceptions

This could explain/predict news sources

Kaiser Health News:

['health law' 'headlines' 'cliff' 'law s' 'kaiserfamfound' 'marketplaces' 'reports today' 'cms' 'reports rt' 'fiscal cliff']

NBC Health:

['safety rules' 'genuine' 'nfl concussion' 'powerful painkiller' 'new safety' 'communion' 'fda proposes' 'bra' 'foster farms' 'november']
BBC Health:

['mps' 'gp' 'ebola video' 'video ebola' 'audio' 'uk ebola' 'care home' 'labour' 'ebola' 'centre']

CBC Health:

['canadian' 'canada s' 'b c' 'canadians' 'p e' 'quebec' 'ebola' 'ford' 'centre' 'facts ebola']

**CNN Health:** 

['rt cnnhealth' 'cnn' 'lost pounds' 'triathlon' 'cnnhealth' 'weightloss' 'lost lbs' 'timehealthland' 'transformation' 'pls']

Everyday Health:

['everydayhealth' 'menshealth' 'jillianmichaels' 'digest' 'rt cspi' 'cspi' 'eatsmartbd' 'psoriasis' 'worldcancerday' 'rt everydayhealth']

Fox News Health:

['disneyland' 'weightloss' 'wakes' 'heart transplant' 'ebola' 'leone' 'sierra leone' 'georgia' 's' 'lodged']

The Guardian Health:

['midwife' 't miss' 'gp' 'day life' 'case missed' 'burnout' 'newsletter' 'andy' 'frontline' 'network s']

Good News Health:

['abs' 'rd' 'weightloss' 'recipes' 'healthyliving' 'fitfluential' 'vacuum' 'greatist' 'gorgeous' 'toned']

LA Times Health:

['cdcgov' 'healthful' 'glutenfree' 'planned parenthood' 'komen' 'rt' 'medi' 'ameracadpeds' 'nejm' 's']

MSN Health:

['clot risk' 'study u' 'gene mutations' 'study' 'heart trouble' 'patients study' 'study study' 's' 'women study' 'blood thinner']

NPR Health:

['npr' 'nprhealth' 'health law' 'ebola' 'health exchanges' 'exchanges' 's' 'insurance website' 'health exchange' 'health']

NYT Health:

['aug' 'briefing' 'op ed' 'nytimes' 'like doctor' 'contributor' 'global health' 'nyt' 'new health' 'letters']

Reuters Health:

['study u' 'mid stage' 'roche' 'eu' 'ebola' 'sanofi' 'abbvie' 'stage study' 'gilead' 'amgen']

US News Health:

['usnews' 'leonardkl' 'rankings' 'rt leonardkl' 'kerigans' 'd love"healthyliving' 'fitness tracker' 'goredforwomen' 'hearthealth']

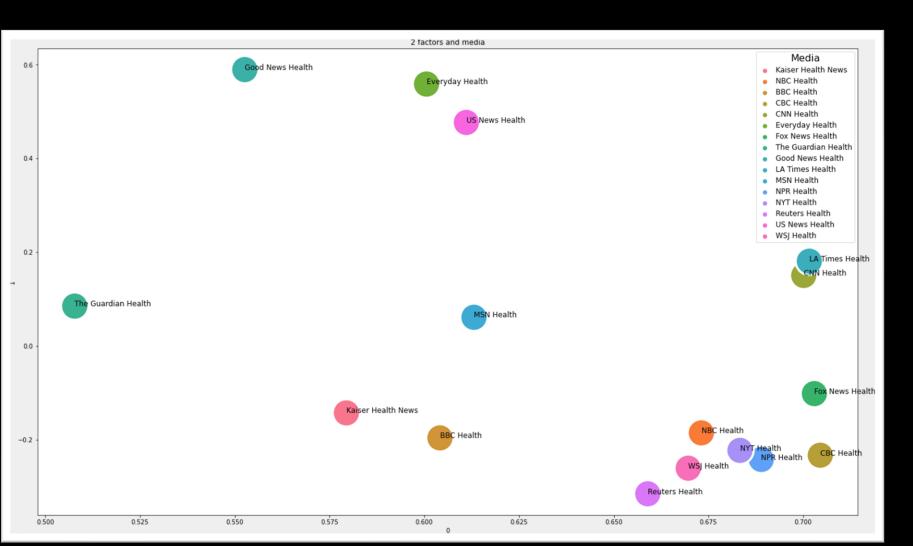
WSJ Health:

['pharma' 'valeant' 'health law' 'h rt' 'wsj' 'allergan' 'abbvie' 'good morning' 'headlines' 'htt rt']

### TF/IDF Based Clustering And Categorization

- Predictive model using the TF/IDF scores was not successful with 30.18% accuracy score even with the training data
- New tweets can be categorized into "closest" source media
  - It is interesting that the model tells what each tweet "looks like"
  - But it does not accurately predict the tweets from the accounts that were in the training set
- TF/IDF vectors categorizes tweets and source accounts, but not suitable for building predictive models

## TF/IDF and MF for Sources



The TFIDF vectors are decomposed with 2 components Matrix Factorization

See if the two factors are latent factors identifying the source medias

Looks to me that

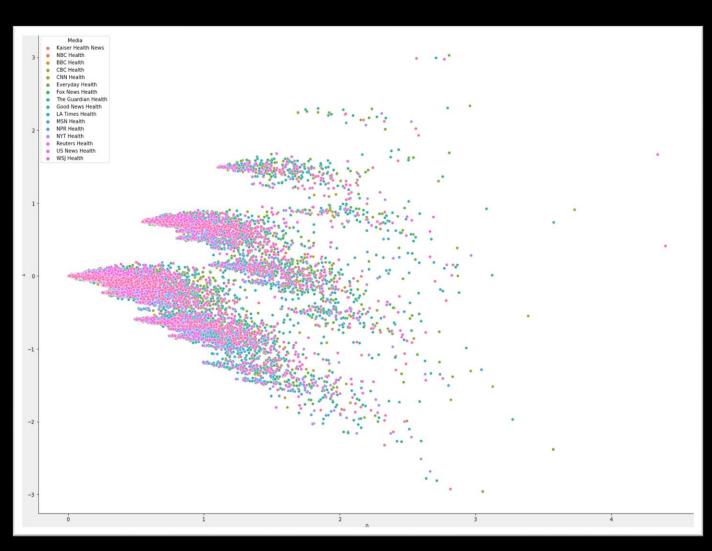
- traditional vs unconventional horizontally (f-0)
- Sensational vs dried vertically (f-1)

### Word Count Vector and MF for Tweets

Created word count vectors and decomposed with 2 components Matrix Factorization on each tweet

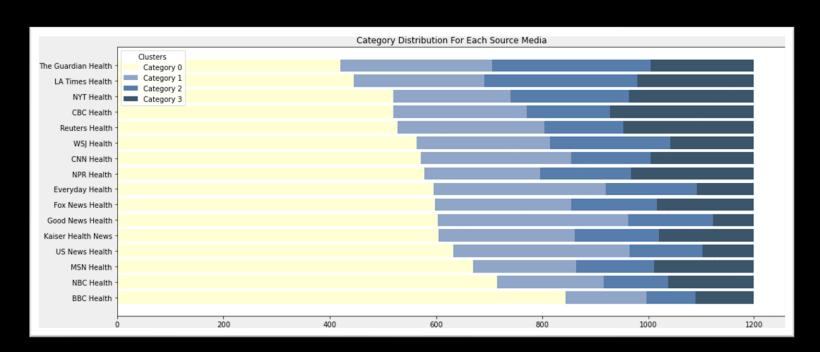
Does not look like it can distinguish the source accounts, but it does cluster tweets

Decided to build a model to cluster tweets based on word count vector and MF



## Tweet Categorization

- Built a model to categorize tweets into 4 categories
- Used Word Count Vectorization, 5 components Matrix Factorization and Kmeans (k=4)
- Tweets from each source account are categorized as shown in the bar chart
- It gives certain evaluations to the source accounts, and categories to the tweets
- Tweets categorization intuitively make sense



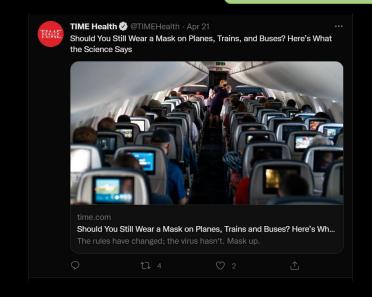
## Evaluation and Conclusion

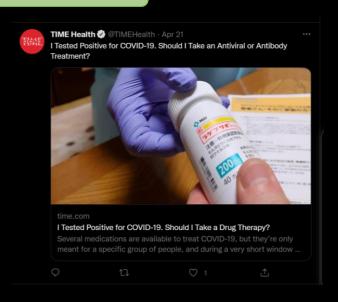
- Tweet texts are too short to make predictive models
- Tweet analysis should include linked pages, images, and hashtags
- Vectorization/Factorization clustering still yields interesting insights
  - It could give certain labels to twitter accounts
  - It could categorize tweets could make a basis for recommendation or curation engines
- For validation of unsupervised model, manual review by multiple individuals is mandatory
- I gave my personal interpretations on the 4 categories
  - Category 0: social matters and policies, Category 1: diseases and illness
  - Category 2: personal health such as diet, Category 3: scientific and medical
  - This was not too bad see what the model said on some tweets today in next 4 slides

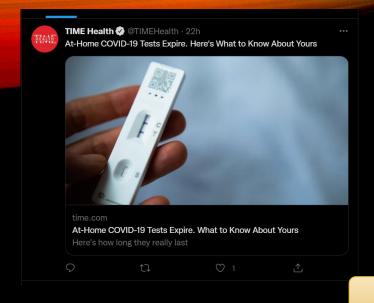




### Category 0: Social and Policies



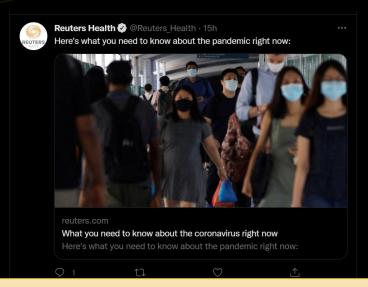




Everyday Health 🔮 @EverydayHealth · 6h

#Bipolar disorder is widely misunderstood, and it's time to clear up those

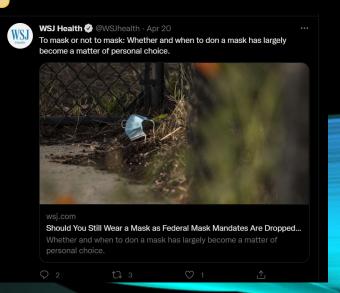
7 Myths and Facts About Bipolar Disorder
One sobering fact about bipolar disorder is that as



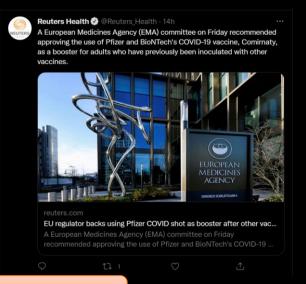


#### Category 1: Diseases and Illness



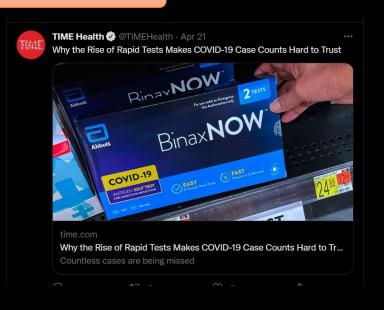






#### Category 2: Personal Health







U.S. News Health 🔮 @USNewsHealth · 1h

These are the Best Children's Hospitals in the nation for neurology and neurosurgery. #BestHospitals



health.usnews.com

These Are the Top Children's Hospitals in the National for Neurology a...

For treating everything from epilepsy to stroke in kids, these medical centers are the best of the best.







1



Amid rising marijuana use in the U.S., researchers are exploring risks to bystanders, children—and pets



wsj.cor

Rising Marijuana Use Presents Risks to Pets, Bystanders

A variety of recent studies have examined the incidental effects of pouse, including one tying its legalization to increased cannabis ...



17 2



1

#### Category 3: Medical Science





bbc.com

Covid cases in Scotland fall by 30,000 in a week

It is the fourth week in a row the number of positives tests has dropped, according to official figures.



17









.@TexasChildrens is the top-ranked hospital in treating high-risk heart defects and helping children with severe congenital heart disease.



health.usnews.cor

Best Hospitals for Children With Severe Congenital Heart Disease

experienced in treating high-risk defects.







