# 

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# Background

## **Fake News Corpus**

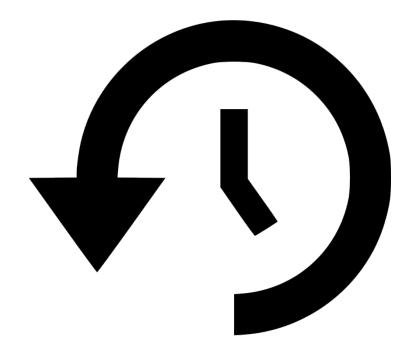
- Labels
  - Fake News
  - Conspiracy Theory
  - Credible
  - Proceed with caution
- Relation between the articles contained
- Likelihood of an article label



# Phase I

## Recap

- Date clean up
- Preprocessing
- Created Vocabulary
- Algorithms
  - o k-means
  - DBSCAN



## **Recap - Preprocessing**

- Text to numerical representation
  - Stop word removal
  - o Stemming PorterStemmer
  - Lowercasing
  - Tokenization
  - Punctuation removal

## **Results**

- Results
  - Sparse data
  - Negative Silhouette Coefficients
- Change of strategy
  - Choose articles
  - Trim subset
  - Change algorithm

# **Phase II**

## Clustering

- k-means
  - Average Silhouette
  - Using *k*=8 resulted in interesting set of clusters
- DBSCAN
  - Find 'good' parameters
  - Minimize noise
  - Distance measures

## Results (k-means)

- 20k word vocab size
- 30k total articles
- Silhouette coefficient: 0.217
- 8 clusters

# Articles	Conspiracy	Fake	Reliable
19671	5499	6209	7885
7174	3168	2981	1025
1845	845	411	589
833	367	299	167
314	83	78	153
181	18	1	162
42	14	14	14
18	6	7	5

Table 1: Eight clusters, with number of articles for each label

## Results (k-means)

#### 2 biggest clusters

- Cluster with 19671 articles: 5529 conspiracy, 6249 Fake, 7893 Reliable
  - Words: 'one', 'state', 'peopl', 'us', 'time', 'would', 'said', 'year', 'like', 'also', 'trump', 'christian'
- Cluster with 7181 articles: 3178 conspiracy, 2969 Fake, 1034 Reliable
  - Words: 'one', 'new', 'state', 'american', 'peopl', 'us', 'time', 'would', 'year', 'like', 'govern'

#### 2 smallest clusters

- Cluster with 18 articles: 6 conspiracy, 7 Fake, 5 Reliable
  - o 'one', 'new', 'state', 'american', 'time', 'would', 'even', 'report', 'year', 'write', 'world', 'like', 'govern', 'iran', '2009'
- Cluster with 64 articles: 25 conspiracy, 21 Fake, 18 Reliable
  - o 'one', 'new', 'state', 'say', 'peopl', 'time', 'would', 'even', 'report', 'year', 'get', 'go', 'like', 'also', 'govern'

## Results (k-means)

#### Interesting clusters

- Cluster with 181 articles: 18 conspiracy, 1 Fake, 162 Reliable
  - o 'se', 'de', 'la', 'lo', 'al', 'el', 'con', 'su', 'un', 'en', 'que', 'para', 'del', 'es'
- Cluster with 290 articles: 77 conspiracy, 72 Fake, 141 Reliable
  - ['war', '-', 'one', 'state', 'american', 'peopl', ''', 'us', 'time', 'would', '"', '"', 'presid', 'also', 'govern']

## Results (DBSCAN)

- Better results with higher *eps* 
  - Decreased amount of noise points
  - Distance measured from noise points to nearest cluster's core points

- Bad metrics
  - Silhouette coefficient
  - Homogeneity

Matrix	Clusters	Noise
15K x 20K	2	4.6%
30K x 20K	3	4.3%

# Phase III

## Model

- Motivation is to get a binary output on whether an article is fake or credible
- Features are our vocabulary with term frequency
- Training data has 10k reliable and 10k fake articles
- 75% train data, 25% test data

## **Linear Regression Results**

• Test accuracy: **66.3**%

• Baseline: 50.0%

• Threshold 0.5

High coefficients	'fortyeight', 'heartach', 'dissoci', 'compatriot', 'harbing', 'valerian', 'mosh', 'cha', '3800', 'turncoat', 'olympia', 'wacko'	
Low coefficients	'transvers', 'claudia', 'manitoba', 'molecular', 'hydrolyz', 'landhold', 'noncompetit', 'gorg', 'conciliatori', 'nazca', 'generalpurpos', 'vino'	

## **Naïve-Bayes**

- Bad results because of features
- Articles used were fake and reliable

## Conclusion

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- Reduced amount of noise in all clusters
- Analysis of cluster data was easier
- Labeling prediction had an accuracy of 66% accuracy
- Deep learning techniques could have better accuracy