SENTIMENT ANALYSIS AND TOPIC DETECTION FOR FAKE NEWS CLASSIFIER

IS424 G3T4

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PROBLEM STATEMENT

The plethora of misleading false information in this time where data is highly accessible causes **confusion** and **frustrations** to both individuals and businesses.

Fast sharing on the internet (social media & news channels)

What do we want to solve?

The Internet's double-edged sword

MOTIVATION

1. Eliminate/ overcome the disadvantages of online news platforms
2. Create a better environment for safe sharing of information
3. Identify what's true and what's false
4. Understand trends in false news

Google Scholar

fake news detection

Fake news detection using naive Bayes classifier

M Granik, V Mesyura - 2017 IEEE First Ukraine Conference on …, 2017 - ieeexplore.ieee.org

This paper shows a simple approach for **fake news detection** using naive Bayes classifier. This approach was implemented as a software system and tested against a data set of Facebook **news** posts. We achieved classification accuracy of approximately 74% on the test …

Cited by 129 Related articles

Naïve bayes classifier

→ There's also SVM and k-NN (most common approaches)

TI-CNN: Convolutional neural networks for **fake news detection**

Y Yang, L Zheng, J Zhang, Q Cui, Z Li… - arXiv preprint arXiv …, 2018 - arxiv.org

… I, cartoons, irrelevant **images** (mis- match of text and **image**, no face in political **news**) and altered low-resolution **images** are frequently observed in **fake news**. In this paper, we propose a TI-CNN model to consider both text and **image** information in **fake news detection** …

Cited by 51 Related articles All 4 versions

Text & image resolution analysis

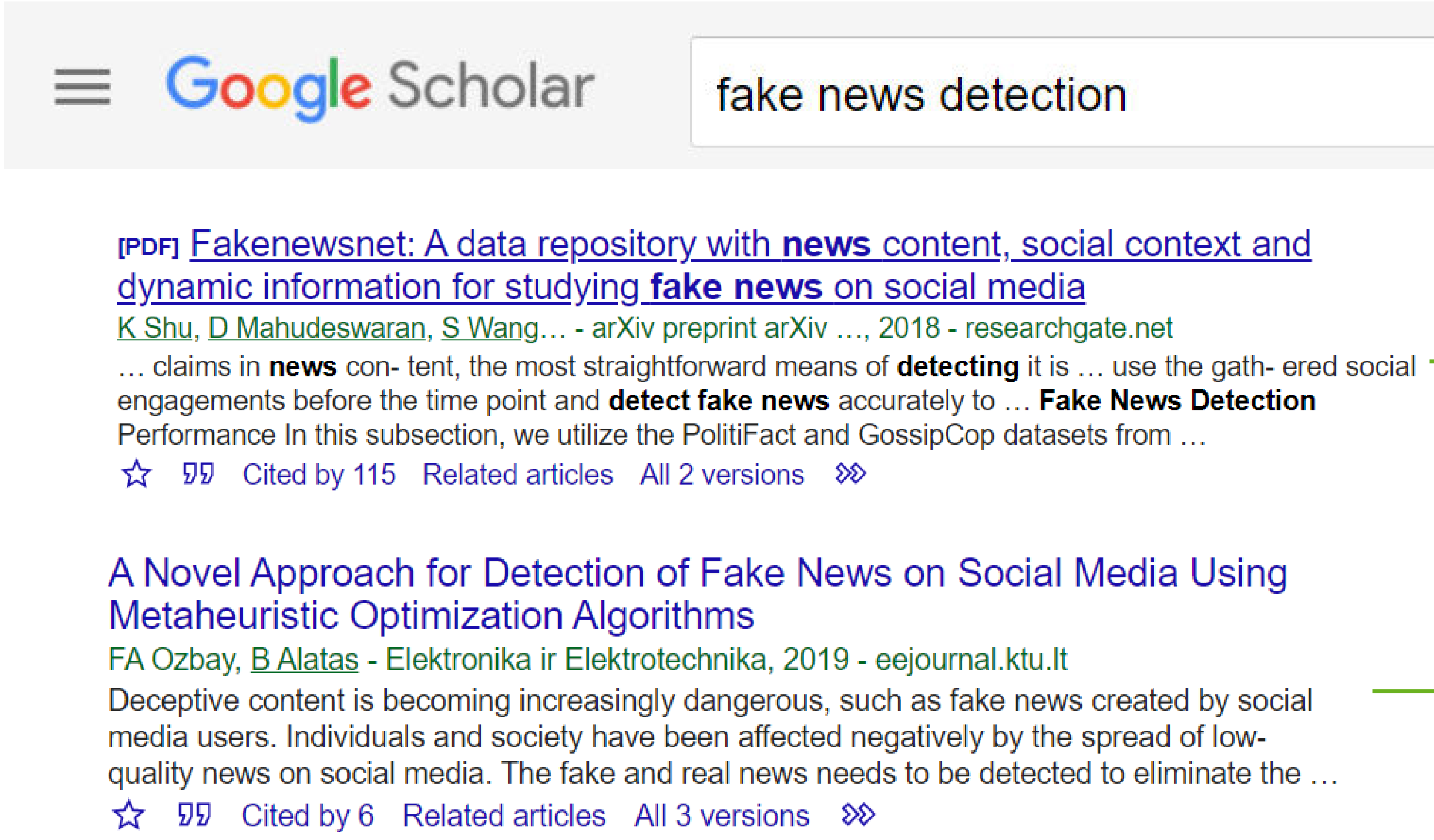
Fake news identification characteristics using named entity recognition and phrase **detection**

HS Al-Ash, WC Wibowo - 2018 10th International Conference …, 2018 - ieeexplore.ieee.org

… Fig. 5. Test results for **Fake News** Category … Fig. 6. Test results for Real **News** Category The term frequency vector representation used as the document feature has performed 2434 correct document classifications for **false** and original **news** of 2516 documents or there is an …

Cited by 9 Related articles All 2 versions

Specified entities detection



Time-based analysis

Shift of focus to optimization using Grey Wolf Optimisation and Salp Swarm Optimisation

Google Scholar

fake news detection with sentiment and topic analysis

Fake news detection on social media: A data mining perspective

K Shu, A Sliva, S Wang, J Tang, H Liu - ACM SIGKDD explorations …, 2017 - dl.acm.org

… **Detecting fake news** on social media poses several new and challenging research problems … Note that few papers exist in the literature that **detect fake news** using social context features … because we believe this is a critical aspect of successful **fake news detection**, we introduce …

Cited by 875 Related articles All 12 versions

Little has been done on feature analysis with text

Supervised learning for **fake news detection**

JCS Reis, A Correia, F Murai, A Veloso… - IEEE Intelligent …, 2019 - ieeexplore.ieee.org

… Our best classification results can correctly **detect** nearly all **fake news** in our data, while misclassifying … 6. K. Shu, A. Sliva, S. Wang, J. Tang, and H. Liu, "**Fake news detection** on social media: A … S. Vosoughi, D. Roy, and S. Aral, "The spread of true and false **news** online," Science …

Cited by 48 Related articles All 9 versions

The study that emphasizes the importance of features in the classification of fake news

Automatic deception **detection**: Methods for finding **fake news**

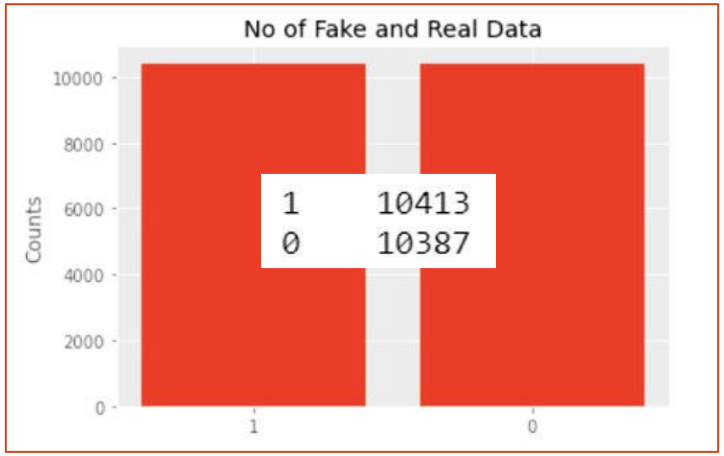
NK Conroy, VL Rubin, Y Chen - Proceedings of the Association …, 2015 - Wiley Online Library

… **Fake** negative reviewers over-produced negative emotion terms relative to the truthful reviews … However, findings emerging from **topic**-specific studies (product reviews, business) may have limited generalizability towards real-time veracity **detection** of **news** …

Cited by 474 Related articles All 8 versions

Emotion analysis & Topic detection

TRAINING AND TESTING DATA – FROM KAGGLE



dropped →

From topic classifier model and sentiment classifier model →

Test dataset is not labelled →

Field Name	Data Type	Description
id	int64	Unique ID for a news article
title	object	The title of a news article
author	object	Author of a news article
text	object	The text content of the article(may be incomplete)
topic	string	Category of news
sentiment	integer	Neutrality from title
label	int64	A label that marks the article as potentially unreliable •1: unreliable •0: reliable

THROWBACK TO PRELIM MODEL

Using count vectorizer

```
Naive Bayes
Accuracy:
0.9009615384615385
Confusion Matrix:
[[2458  376]
 [ 139 2227]]
Time taken:
0:00:00.081786
```

Score: 0.90357

```
SVM
Accuracy:
0.9403846153846154
Confusion Matrix:
[[2428  141]
 [ 169 2462]]
Time taken:
0:00:24.593326
```

Score: 0.94423

```
Logistic Regression
Accuracy:
0.9511538461538461
Confusion Matrix:
[[2456  113]
 [ 141 2490]]
Time taken:
0:00:08.818853
```

Score: 0.95027

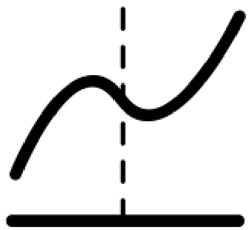
```
Decision tree
Accuracy:
0.8873076923076924
Confusion Matrix:
[[2304  293]
 [ 293 2310]]
Time taken:
0:00:11.561091
```

Score: 0.89478

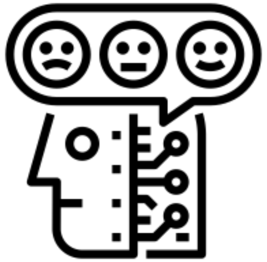
```
Random forest
Accuracy:
0.9101923076923077
Confusion Matrix:
[[2447  317]
 [ 150 2286]]
Time taken:
0:00:35.617632
```

Score: 0.90521

METHODOLOGY OVERVIEW

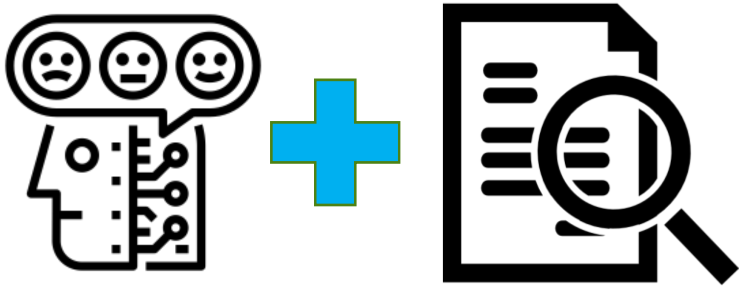


Logistic Regression for Classifying Fake News (Baseline Model)



Sentiment Analysis using TextBlob and Vader

Topic Detection using K-Means and LDA



Combine Outputs from Sentiment Analysis and Topic Detection

Training models based on combined outputs.
(E.g. Text + TextBlob + K-Means, Text +Vader + LDA)

Run predictions on test dataset for each model and compare their accuracy against baseline model

SENTIMENT ANALYSIS

TEXTBLOB

- A library simplifying text processing tasks. It provides properties for classification, part-of-speech tagging, noun phrase extraction, sentiment analysis
- **What we use:** 'Sentiment' property is used to capture the emotions embedded, ascertain the subjectivity of the textual information
- **What we want to find: Polarity** measures emotional level from negative to positive[-1.0, 1.0]
  Subjectivity measures agreement level from highly objective to highly subjective [0.0, 1.0]
- e.g. train['tb_pol'] = [b.sentiment.polarity for b in desc_blob]

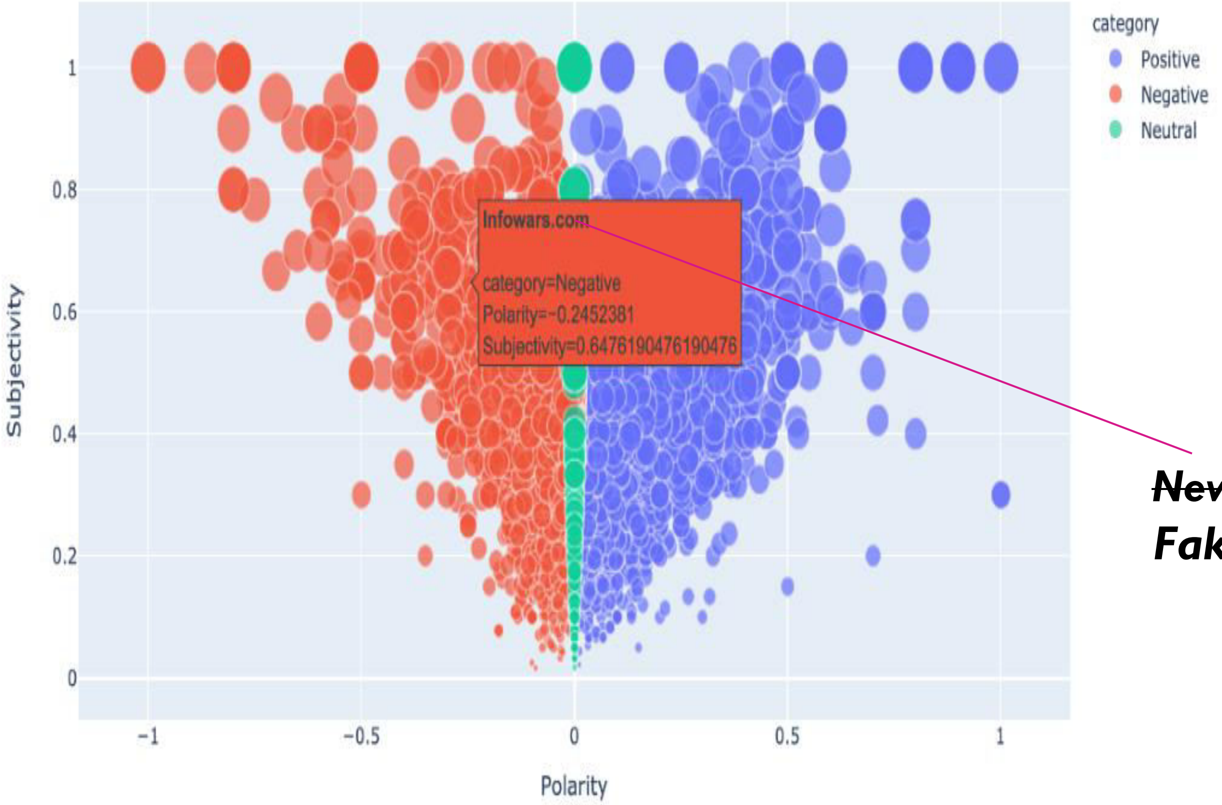
tb_Pol	tb_Subj	Polarity_category
0.026726	0.456226	2
0.077613	0.485211	2
0.083994	0.418484	2
0.021485	0.251616	2
0.047143	0.197143	2

VADER

- VADER (Valence Aware Dictionary and Sentiment Reasoner) is a lexicon and rule-based sentiment analysis tool that is *specifically attuned to sentiments expressed in social media*
- 'polarity_scores()' method is used to capture the emotions embedded, which gives negative, neutral, positive, compound
- **What we want to find:** Vader's compound score is *normalised between −1 to 1, by picking up intrinsic emotion category of each word*
- e.g. train['text_vader_compound'] = [analyser.polarity_scores(v)['compound'] for v in train_copy['text']]

text_vader_compound
0.5431
-0.4405
0.9853
-0.9993
-0.9517

LET'S MODEL IT! – SENTIMENT ANALYSIS



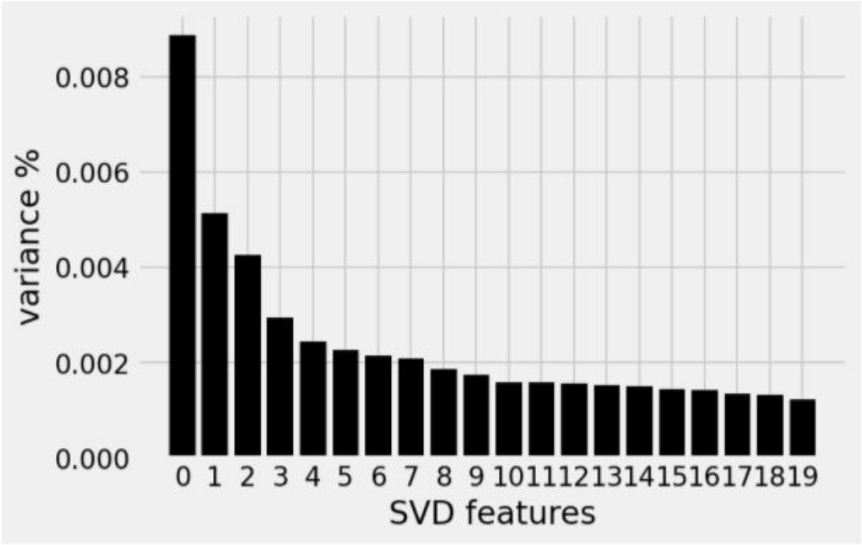
~~News...?~~
Fake News!!!!!

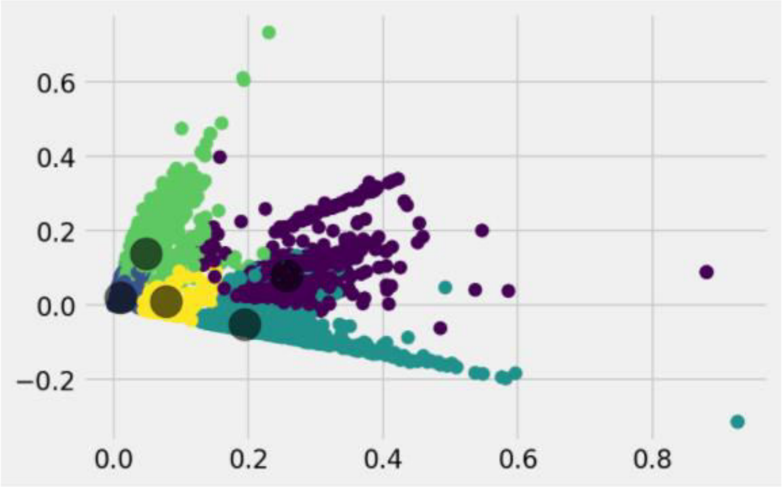
compound	neg	neu	pos
0.5431	0.050	0.888	0.062
-0.4405	0.068	0.867	0.065
0.9853	0.111	0.755	0.134
-0.9993	0.244	0.721	0.035
-0.9517	0.125	0.849	0.026
0.9537	0.080	0.783	0.137

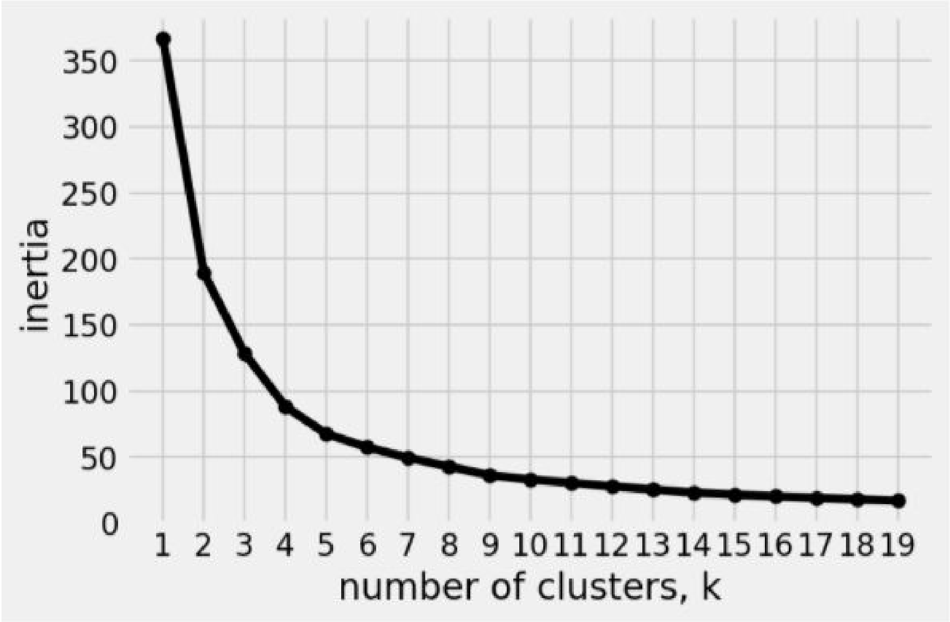
TOPIC MODELLING

K-MEANS

- Tf-idf the Text data
- Run it through SVD
- Select number of cluster
- Run Kmeans







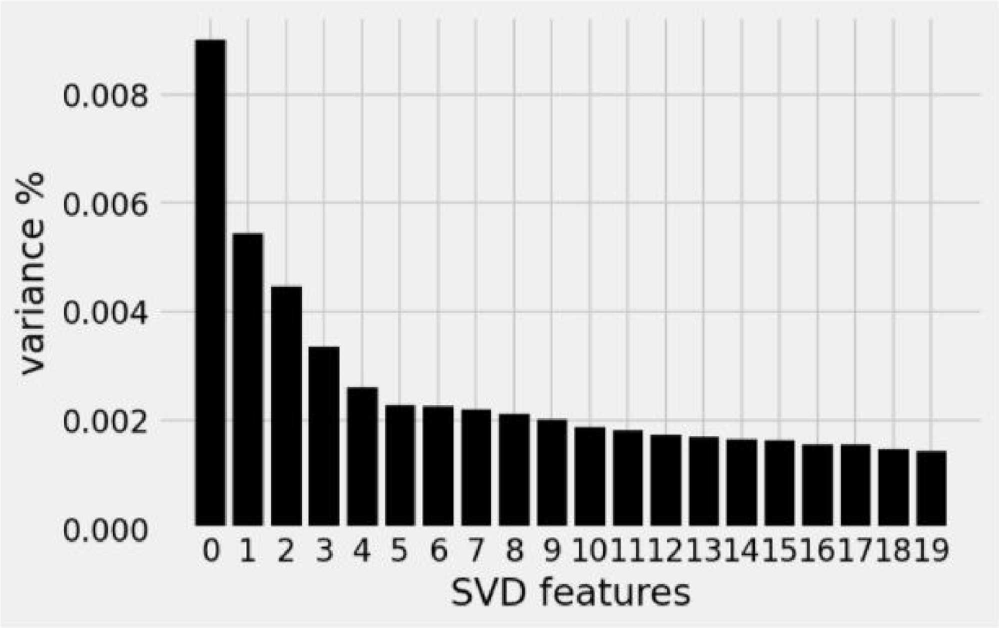
Clustering

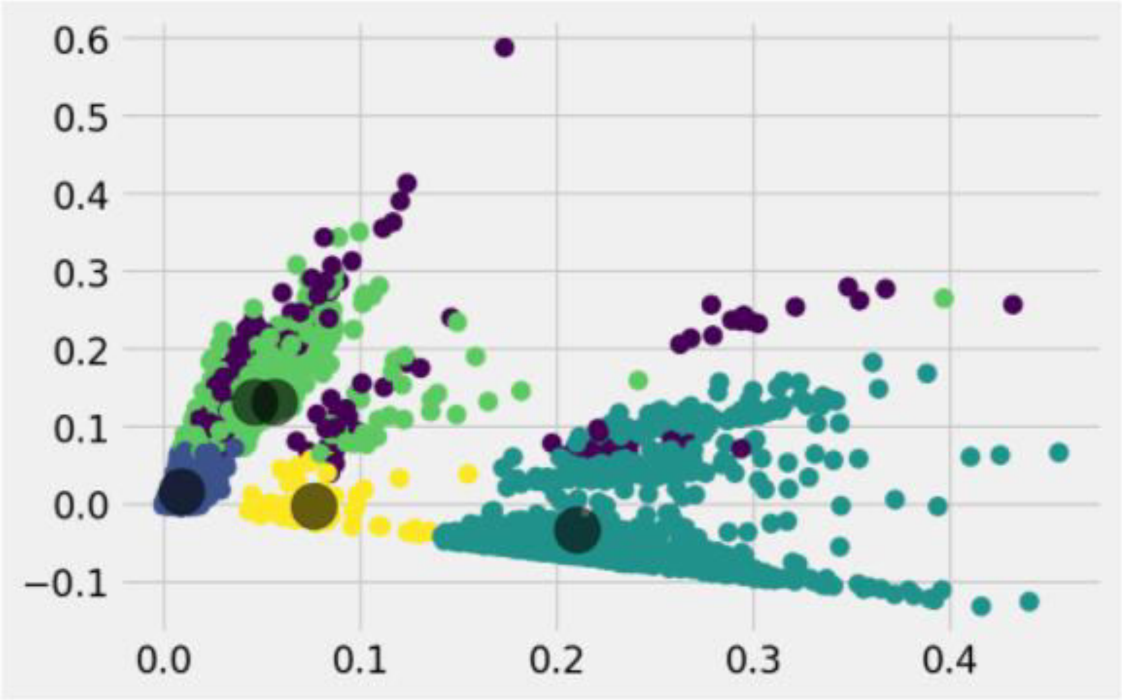
	id	title	author	text	label	K_means
0	0	House Dem Aide: We Didn’t Even See Comey’s Let...	Darrell Lucus	House Dem Aide: We Didn’t Even See Comey’s Let...	1	2
1	1	FLYNN: Hillary Clinton, Big Woman on Campus - ...	Daniel J. Flynn	Ever get the feeling your life circles the rou...	0	1
2	2	Why the Truth Might Get You Fired	Consortiumnews.com	Why the Truth Might Get You Fired October 29, ...	1	2
3	3	15 Civilians Killed In Single US Airstrike Hav...	Jessica Purkiss	Videos 15 Civilians Killed In Single US Airstr...	1	2
4	4	Iranian woman jailed for fictional unpublished...	Howard Portnoy	Print An Iranian woman has been sentenced to ...	1	2

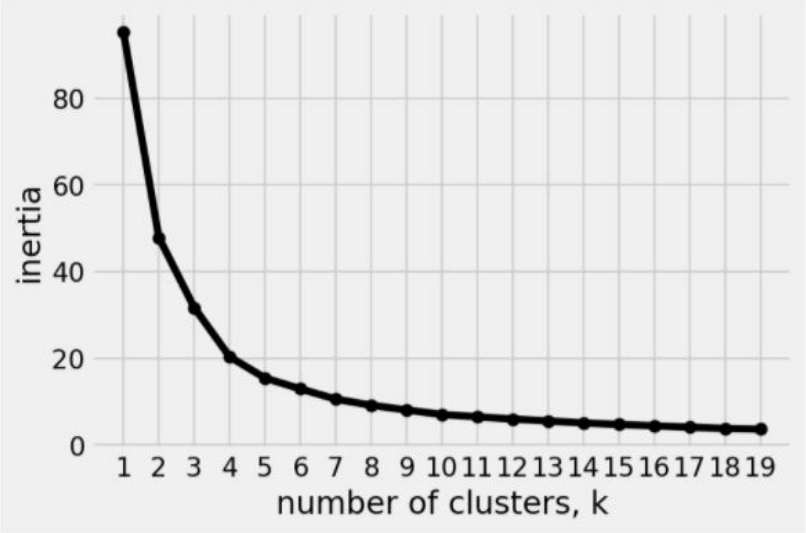
```
In [33]: train.K_means.unique()

Out[33]: array([2, 1, 4, 3, 0])
```

	K_means
0	1114
1	1656
2	10298
3	5073
4	2659





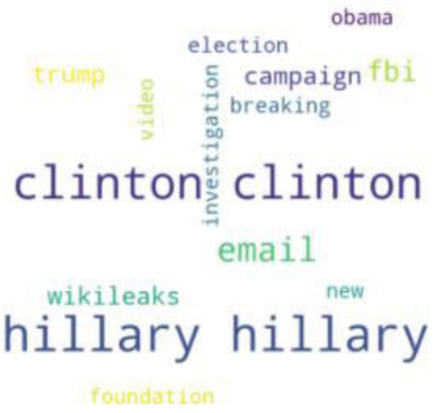


	K_means
0	1312
1	2458
2	386
3	790
4	254

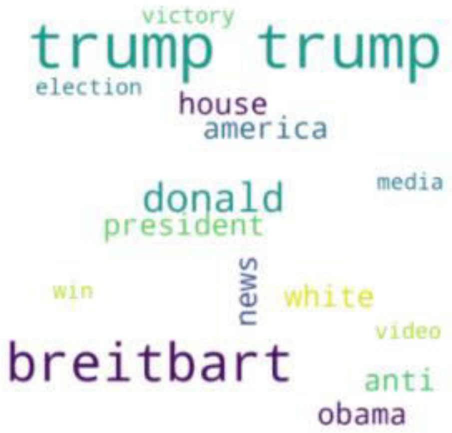
TOPICS FROM K-MEANS (WORDCLOUD-TRAIN)

News published by brietbart about the police, war and elections, related to Russia and America

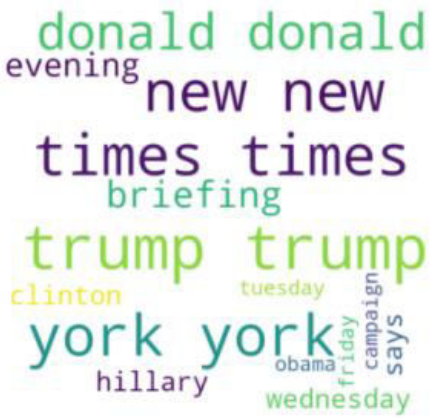
News published by the New York times about the police, China and Obama.



News regarding the investigations by the FBI regarding Hillary Clinton during the election campaigns.

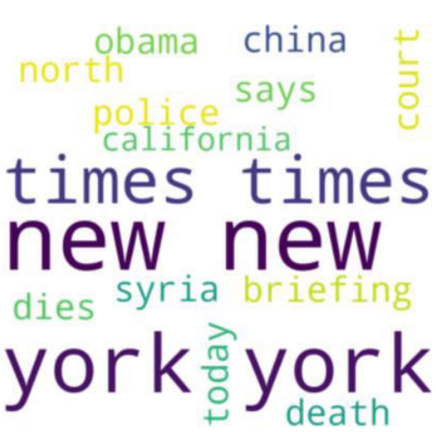


News published by brietbart about the American presidency elections involving trump, racism and winning



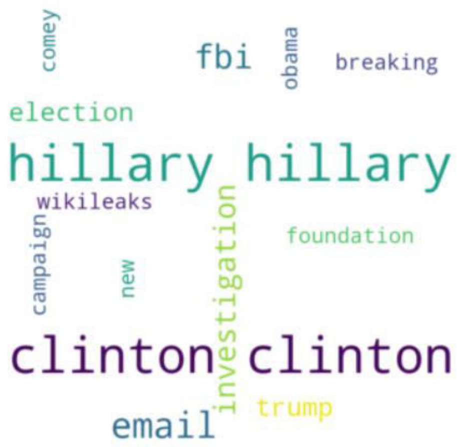
News published by the New York times about Donald Trump.

TOPICS FROM K-MEANS (WORDCLOUD-TEST)

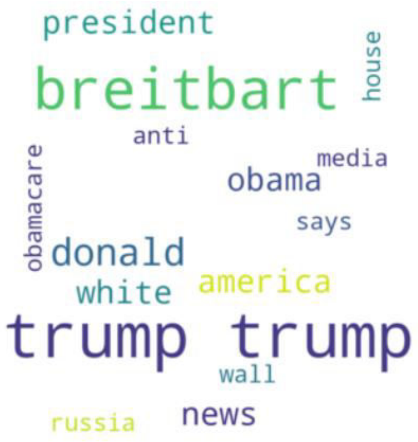


News published by the New York Times about a court case that involves death in north California

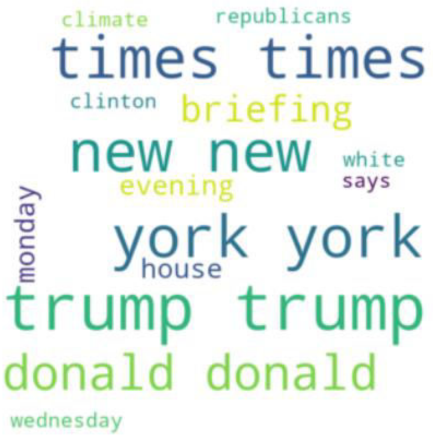
News published by breitbart about the war and elections between Russia and America



Investigations on Hillary Clinton regarding campaign and wikileaks



News published by Brietbart about Trump and what he has to say about obamacare



News published by the New York Times about Donald Trump

LDA- A PROBABILISTIC MODEL

- From our k-means analysis: n_topics = 5
- Input data {id: text}; text → vectorizing with corpus
- Extract dominant topic for clustering, infer from the topic's % contribution via keywords

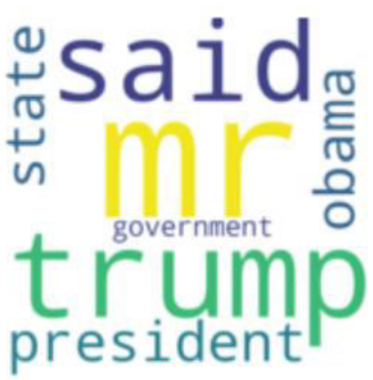
Probabilities per topic

	0	1	2	3	4
0	0.248891	0.000425	0.749842	0.000426	0.000417
1	0.098984	0.000550	0.695024	0.204905	0.000537
2	0.548927	0.040569	0.409936	0.000287	0.000281
3	0.906194	0.023575	0.000673	0.068897	0.000660
4	0.475192	0.002491	0.077013	0.442824	0.002480
...	...	...	...	...	...
20795	0.061002	0.001043	0.678715	0.258214	0.001027
20796	0.000340	0.000339	0.000339	0.998649	0.000333
20797	0.000423	0.536638	0.000420	0.462107	0.000413
20798	0.995354	0.001168	0.001161	0.001170	0.001146
20799	0.057710	0.659799	0.250428	0.031789	0.000275

20800 rows × 5 columns

```
import gensim
docs = [[token.lower() for token in
gensim.utils.tokenize(gensim.parsing.preprocessing.remove_stopwords(d
oc))] for doc in starwars_episodes.values()]
vocab = gensim.corpora.Dictionary(docs)
bow_corpus = [vocab.doc2bow(doc) for doc in docs]
lda_model = gensim.models.LdaMulticore(bow_corpus, num_topics =
n_topics, id2word = vocab, passes = 10, workers = 2)
```

5 TOPICS FROM LDA (WORDCLOUD – TRAIN)



Things said by presidents trump and Obama about state

Yearly statistical information about companies

News about Clinton and trump about people

News reports about new information said (secondary) “he said, she said”

News text in foreign language

5 TOPICS FROM LDA (WORDCLOUD – TEST)

Secondary information about people regarding new topics “he said, she said”

Things president trump said

News regarding trump and Hillary Clinton during the election, about the election and people (perhaps policies)

News text in foreign language

World news regarding government and war in Russia and Syria

CLUSTERING ON TRAIN & TEST DATA

Train set LDA counts

	LDA_Dominant_Topic
0.0	6598
1.0	2711
2.0	6668
3.0	4347
4.0	476

News about Clinton and Trump about people

Test set LDA counts

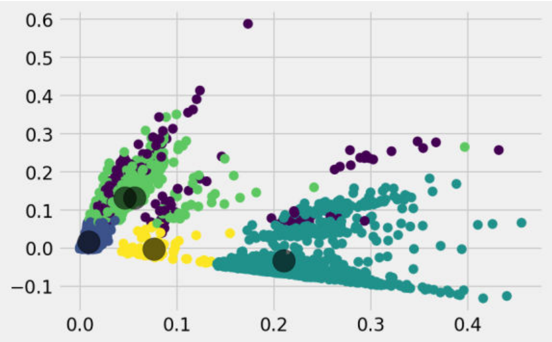
	LDA_Dominant_Topic
0.0	1009
1.0	1955
2.0	1318
3.0	61
4.0	857

Things president Trump said

LET'S MODEL IT! - TOPIC DETECTION

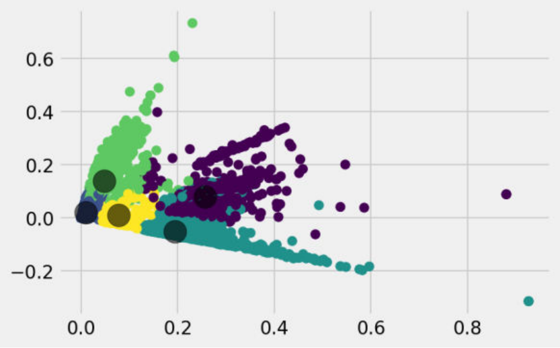
Attribute	K-Means	Latent Dirichlet Allocation
# clusters	{0,1,2,3,4} → 5	{3,4,5,6,7} → 5
Vectorizer	tf-idf	Gensim corpus (bag of words)

K-means

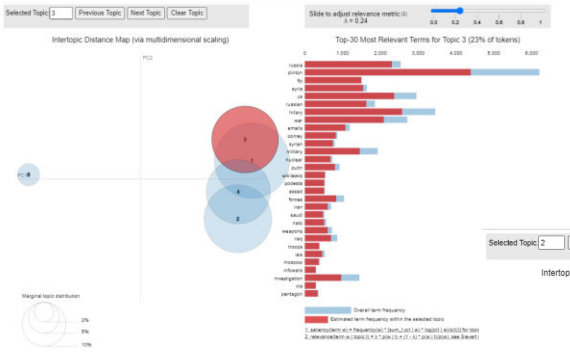


Test Data

Train 'Data

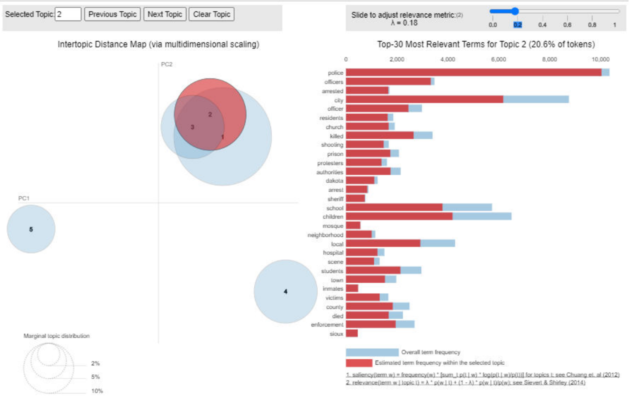


LDA



Test Data

Train Data



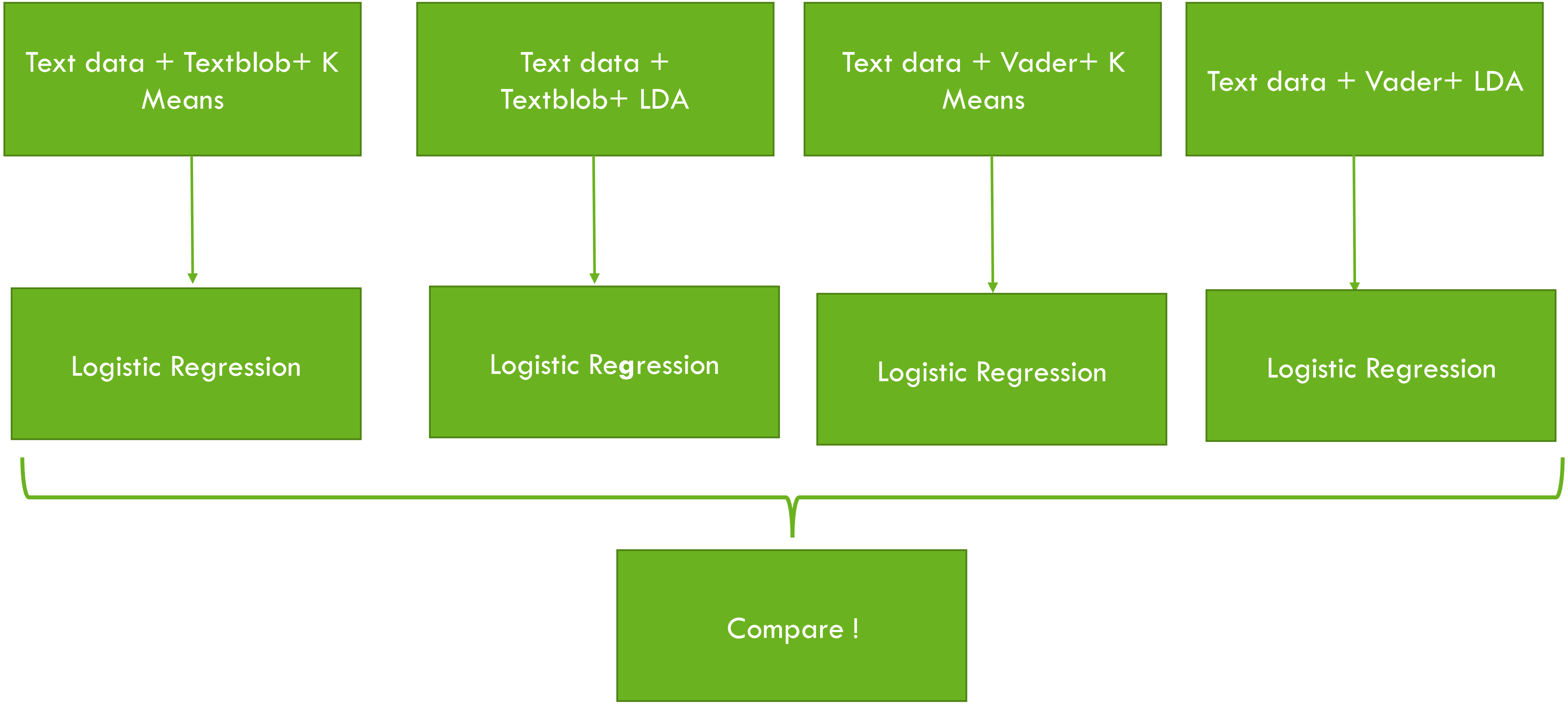
METHODOLOGY FOR "IMPROVED" MODEL

- Label encoder for Polarity Category [Textblob] [Ordinal data]
- For LDA and Kmeans – One hot encoding [Nominal data]
- Text data – Preprocess data then count vectorizer
- Add text data together with the Topic model and sentiment analysis features in a matrix format as Input to Logistic regression model

	id	title	text	K_means	label	LDA_Dominant_Topic	text_vader_compound	tb_Pol	tb_Subj	Polarity_category
0	0	House Dem Aide: We Didn't Even See Comey's Let...	House Dem Aide: We Didn't Even See Comey's Let...	2	1	2.0	0.5431	0.026726	0.456226	2
1	1	FLYNN: Hillary Clinton, Big Woman on Campus - ...	Ever get the feeling your life circles the rou...	1	0	2.0	-0.4405	0.077613	0.485211	2
2	2	Why the Truth Might Get You Fired	Why the Truth Might Get You Fired October 29, ...	2	1	0.0	0.9853	0.083994	0.418484	2
3	3	15 Civilians Killed In Single US Airstrike Hav...	Videos 15 Civilians Killed In Single US Airstr...	2	1	0.0	-0.9993	0.021485	0.251616	2
4	4	Iranian woman jailed for fictional unpublished...	Print \nAn Iranian woman has been sentenced to...	2	1	0.0	-0.9517	0.047143	0.197143	2

```
(<20800x110477 sparse matrix of type '<class 'numpy.int64'>'
        with 5316572 stored elements in Compressed Sparse Row format>,
 <5200x110477 sparse matrix of type '<class 'numpy.int64'>'
        with 1336821 stored elements in Compressed Sparse Row format>)
```

```
(<20800x110483 sparse matrix of type '<class 'numpy.float64'>'
        with 5354034 stored elements in Compressed Sparse Row format>,
 <5200x110483 sparse matrix of type '<class 'numpy.float64'>'
        with 1346254 stored elements in Compressed Sparse Row format>)
```


Text data + Textblob+ K Means
Text data + Textblob+ LDA
Text data + Vader+ K Means
Text data + Vader+ LDA
Logistic Regression
Logistic Regression
Logistic Regression
Logistic Regression
Compare !

RESULTS(BUILD FROM BASELINE MODEL)

```
Logistic Regression Textblob kmeans
Accuracy:
0.9573076923076923
Confusion Matrix:
[[2477  120]
 [ 102 2501]]
Time taken:
0:00:06.516537
```

Score: 0.94752

```
Logistic Regression Textblob LDA
Accuracy:
0.9509615384615384
Confusion Matrix:
[[2461  136]
 [ 119 2484]]
Time taken:
0:00:07.042169
```

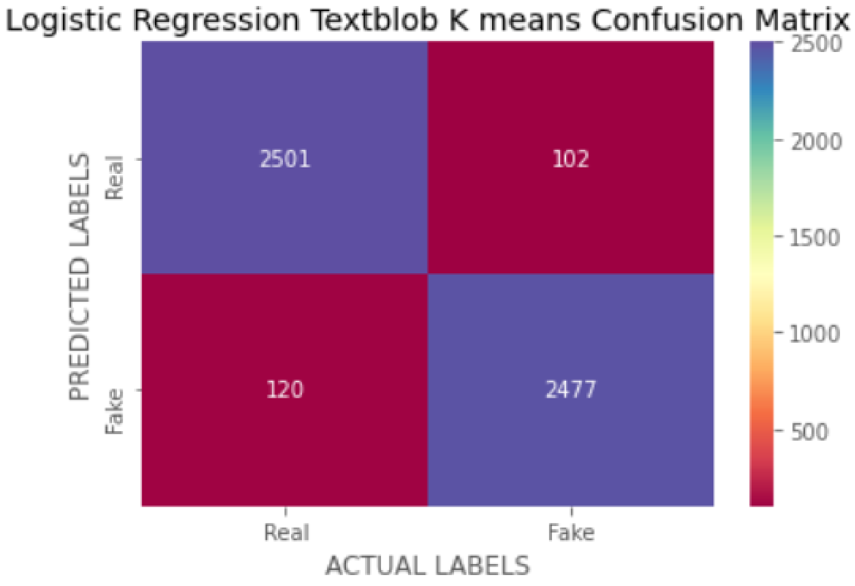
Score: 0.95000

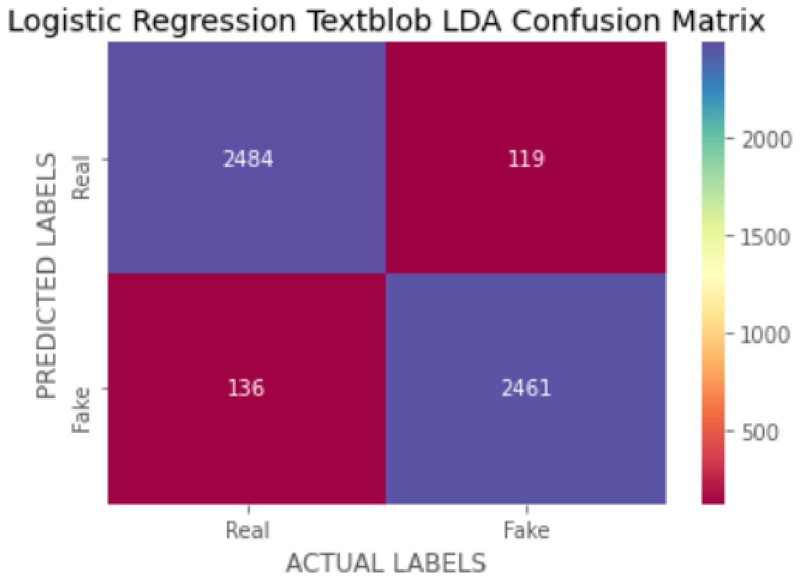
```
Logistic Regression Vader K means
Accuracy:
0.9582692307692308
Confusion Matrix:
[[2478  119]
 [  98 2505]]
Time taken:
0:00:06.331042
```

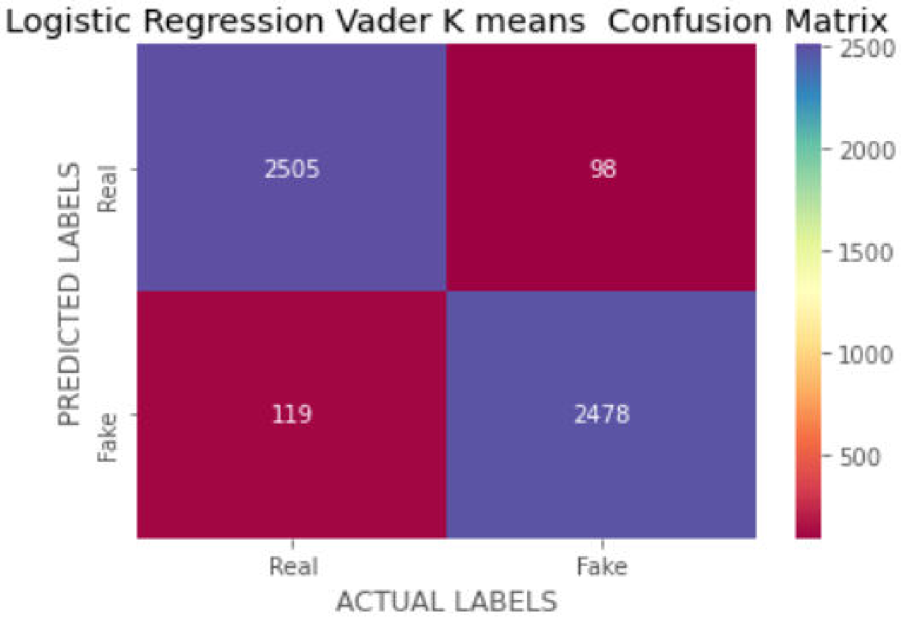
Score: 0.94862

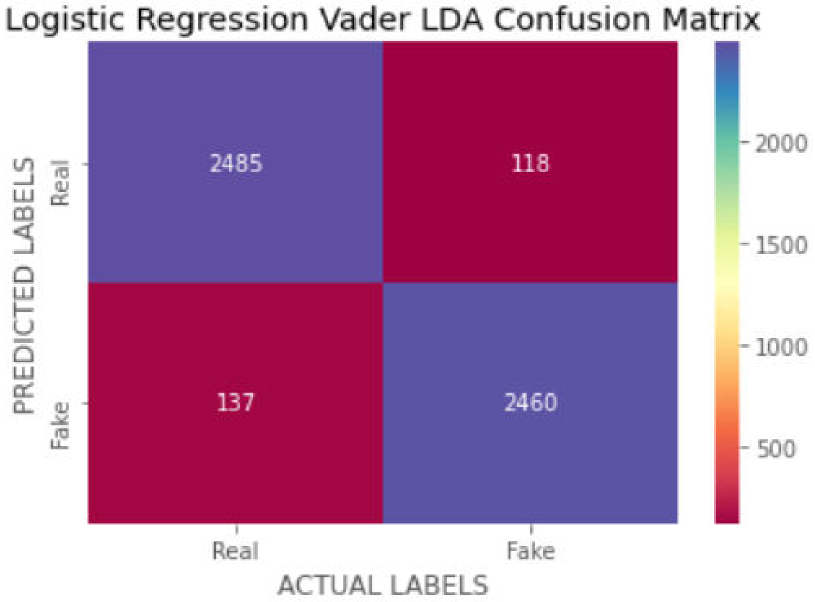
```
Logistic Regression Vader LDA
Accuracy:
0.9509615384615384
Confusion Matrix:
[[2460  137]
 [ 118 2485]]
Time taken:
0:00:06.689116
```

Score: 0.95054


Logistic Regression Textblob K means Confusion Matrix
PREDICTED LABELS
Real
Fake
2501
102
120
2477
Real
Fake
ACTUAL LABELS
2500
2000
1500
1000
500


Logistic Regression Textblob LDA Confusion Matrix
PREDICTED LABELS
Real
Fake
2484
119
136
2461
Real
Fake
ACTUAL LABELS
2000
1500
1000
500


Logistic Regression Vader K means Confusion Matrix
PREDICTED LABELS
Real
Fake
2505
98
119
2478
Real
Fake
ACTUAL LABELS
2500
2000
1500
1000
500


Logistic Regression Vader LDA Confusion Matrix
PREDICTED LABELS
Real
Fake
2485
118
137
2460
Real
Fake
ACTUAL LABELS
2000
1500
1000
500

SO... DID IT WORK?

- Insignificant increase of accuracy in fake news detection as compare to the baseline model
- Improved understanding of the topics and sentiment within dataset

Baseline model	Logistic Regression (Vader + LDA)
Logistic Regression Accuracy: 0.9511538461538461 Confusion Matrix: [[2456 113] [141 2490]] Time taken: 0:00:08.818853 Score: 0.95027	Logistic Regression Vader LDA Accuracy: 0.9509615384615384 Confusion Matrix: [[2460 137] [118 2485]] Time taken: 0:00:06.689116 Score: 0.95054

FUTURE WORK

- Explore other attributes for better accuracy!
- Pass features to NN as input to see if accuracy will increase !

Warning: 99.9% Fake

Chinese leader Xi Jinping was handed a golden opportunity when Donald Trump won the White House. Then it all went wrong.

Are you sure you want to share this?

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